How Does Built Environment Affect Cycling?

Evidence From The Whole California 2010-2012

by

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ABSTRACT

It has been identified in the literature that there exists a link between the built environment and non-motorized transport. This study aims to contribute to existing literature on the effects of the built environment on cycling, examining the case of the whole State of California. Physical built environment features are classified into six groups as: 1) local density, 2) diversity of land use, 3) road connectivity, 4) bike route length, 5) green space, 6) job accessibility. Cycling trips in one week for all children, school children, adults and employed-adults are investigated separately. The regression analysis shows that cycling trips is significantly associated with some features of built environment when many socio-demographic factors are taken into account. Street intersections, bike route length tend to increase the use of bicycle. These effects are well-aligned with literature. Moreover, both local and regional job accessibility variables are statistically significant in two adults' models. However, residential density always has a significant negatively effect on cycling trips, which is still need further research to confirm. Also, there is a gap in literature on how green space affects cycling, but the results of this study is still too unclear to make it up. By elasticity analysis, this study concludes that street intersections is the most powerful predictor on cycling trips. From another perspective, the effects of built environment on cycling at workplace (or school) are distinguished from at home. This study implies that a wide range of measures are available for planners to control vehicle travel by improving cycling-level in California.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

As Robin Chase stated, “Transportation is the center of the world! It is the glue of our daily lives. When it goes well, we don't see it. When it goes wrong, it negatively colors our day, makes us feel angry and impotent, curtails our possibilities” (as cited in Schawbel, 2012). In the last decades, most transportation policies focused on automobiles and highways that generated dynamic influences on the growth of population and spatial allocation economic activities in the rapid expansion of metropolitan areas. A number of issues in the environment, energy, and sustainability are caused by automobile dominant transport policies. Thus, fundamental paradigm changes in transportation planning have been sought, especially in alternative transportation modes.

As an active travel mode, cycling is playing an important role in encouraging a modal shift from private car to public transport. Participation in bicycling has many significant benefits. Firstly, cycling is financially affordable and physically possible by almost everyone (Pucher & Dijkstra, 2003). Secondly, cycling is a fast option for short-distance trips, with smaller physical footprint than driving vehicles. A particular example is that, in traffic congestion cyclists might find alternative ways to speed up their journey, including risky choices as filtering past traffic to jumping red lights (Christmas et al., 2010). More importantly, cycling is no pollution and no nonrenewable resources generated, which makes contributions to environmental protection, fuel consumption, and public health.

Heavy reliance on vehicle mode are risky for public health, and evidence of the health-enhancing potential of cycling is mounting (Moudon et al., 2005). Research focusing physical activity has moved away from vigorous activities to moderate-intensity activities (Pikora et al., 2003). Cycling will provide exercise that reduces medical costs and controls the possibilities of unhealthy situations in daily life, such as high blood pressure, high cholesterol, obesity, and metabolic syndrome. A number of studies address the importance of active travel to the health of different types of people, especially to adolescent and elderly (Beenackers et al., 2012; Bruijn et al., 2005; Cervero et al., 2009; Cui et al., 2014; Forsyth et al., 2007&2009; Frank et al., 2005; Fraser&Lock, 2011; Handy et al., 2002; Heesch et al., 2012; Kerr et al., 2006). For instance, Bruijin et al. (2005) conducted research to investigate the correlations between bicycle usage for transportation and snacking behavior in a Dutch adolescent case. Obviously, physical activity for daily travel may help burn up calories and help them avoid the problems of overweight and obesity.

From another perspective, the link between urban structures and human activities has long been of interests to the field of urban planning (e.g. Handy et al., 2002). Built environments represent micro-level land use pattern (e.g. Lee, 2006). Through quantifying methods, numerous studies support that different physical built environment characteristics such as residential density, street connectivity, land use mix, neighborhood safety and aesthetics, will generate different impacts on non-motorized transport (e.g. Wendel-Vos et al., 2007; Owen et al., 2004; Heath et al., 2006; Frank et al., 2005; Handy et al., 2002; Winter et al., 2010; Zhao, 2014). This study adds to this literature, by investigating the correlations between objective built environments and cycling behavior using an unusually large travel survey and built environment features dataset from California.

1.2 Problem Statement

Cycling is a sustainable transportation option with great growth potential in North America. In addition, cycling can attractively combine travel and physical activity and economically cover longer distances than walking (Moudon et al., 2005). To comply with SB375, a 2008 state law, California local and regional governments are working to develop and implement new policies that aim to reduce vehicle miles traveled (VMT) (Salon, 2014). That is because the average miles traveled per vehicle might cause severe environmental issues, such as be directly proportional the amount of carbon emissions being produced and reducing them will lead to a slow rate of environmental damages. Encouraging people to ride a bicycle is a good strategy to achieving this goal. California statutory language has specifically targeted to establish new bicycle transportation system and fulfill the functional needs of bicycle commuters. A number of public and private organizations have been involved to follow the call of state law.

Funding for many California bike projects is provided by the California Bicycle Transportation Account. This account comes from the Motor Vehicle Fuel License Tax and Highway Users Tax Account. Due to 2008, funding has been increased to $7.2 million per year and available to counties, cities and nonprofit entities (Shinkle & Teigen, 2008). Indeed, this plan should have its own strategic objectives, which reveals that the Bicycle Transportation Plan should be a long term project of at least more than five years, as strategic goals are visionary and consider sustainability as opposed to short term targets. Also, the state of California needs a long term direction to manage and solve its issue of rising traffic pollution. Such social action as identified above has been taken in local and regional context. However, there is few studies to analyze the correlations between achieving the goals of such plan and improving local physical built environments in California.

1.3 Research Questions

The overarching research question in this study is “how does built environment affect cycling in California?” Answers to this question will facilitate planning and policy interventions to create better cycling environment in California. This study quantifies the characteristics of the built environment into six groups, and their impacts on cycling behavior will be tested (positive, negative or unclear). During the whole process, socio-demographic attributes are controlled as the explanatory variable, which may act as significant predictors for active travel as cycling. Moreover, this study considers three different location types that may be relevant to travel behavior: home, school, and workplace. The goal of this thesis is to add new findings to the literature on how these physical built environment factors affect cycling in the context of the California State from 2010 to 2012.

1.4 Thesis structure

Section 1 introduces the motivation to conduct this study and current transportation problems in California. Research questions are put forward based on the introduction, together with research scopes for this study. Section 2 mainly reviews the literature about how each group of built environment factors affects cycling. The following Section conducts descriptive analysis, regression analysis and elasticity analysis for this study case, especially focuses on exploring data characteristics. In this core Section, applied econometrics models are also presented with a brief review of data measurements in the literature. This study ends up with a conclusion to facilitate the interpretation of research results for planning and policy interventions that control VMT and promote cycling environment in California.

CHAPTER 2

LITERATURE REVIEW

2.1 “D Measures” VS. Socio Ecological Framework

Many researchers have defined built environment in a variety of ways. In 2003, Pikora et al. (2003) summarized a social ecological conceptual framework, which might be treated as a basic methodology to investigate the relationships between built environment attributes and cycling levels in USA. In this conceptual framework, physical environmental features are categorized as “Functional, Safety, Aesthetic and Destination” (Table 2.1 – 1).

Table 2.1 – 1 Social ecological framework

Category	Definition
Functional	The functional feature relates to the physical attributes of the street and path that reflect the fundamental structural aspects of the local environment.
Safety	The safety feature reflects the need to provide safe physical environments for people.
Aesthetic	The presence, condition and size of trees; the presence of parks and private gardens; the level of pollution; and the diversity and interest of natural sights and architectural designs within the neighborhood.
Destination	The destination features relate to the availability of community and commercial facilities in neighborhoods.

(Source: Pikora et al., 2003)

Saelens et al. (2003) supplemented some other items for fundamental transportation as well as urban design and planning that relevant to walking or cycling for transport. That is, non-motorized transport could serve as a performance indicator to aid New Urbanism and Smart Growth. The American Planning Association (2002) defined Smart Growth as ‘‘the planning, design, development and revitalization of cities, towns, suburbs and rural areas to create and promote social equity, a sense of place and community, and to preserve natural as well as cultural resources’’(as cited in Handy et al., 2005). Land use policies in smart growth programs include mixed-use zoning, infill development, brownfield development, and transit-oriented development, as well as bicycle and pedestrian infrastructure. Handy et al. (2005) mentioned that smart growth strategies would bring residents closer to destinations and provide viable alternatives to driving, and thus help reduce automobile use.

However, scholars in transportation planning are always exploring research on this topic from another perspective. In previous travel studies, such influences that generated by land use on cycling have usually been named with words beginning with D. Firstly, the concept of "3D" – density, diversity and design are advanced by Cervero and Kockelman (1997). Most studies are following this original concept in walking and cycling research field. In 2001, this "3D" model was extended to "5D" model by adding two additional "Ds": distance to transit and destination accessibility. "Ds" models are widely used in a global scale beyond North American and Europe. For example, Cervero et al. (2009) applied a "5D" model to investigate the influences of built environments on walking and cycling in Bogota, Colombia – the capital of a developing country, where is well known for its sustainable urban transport systems. However, the results of this study seem unsatisfactory because most factors in "5Ds" on non-motorized travel failed to achieve statistical significance. Whether "D measures" are generalizable to other large cities in developing world has been another argument (Cervero et al., 2009; Zhao, 2014). To date, the original "3D" concept has been developed to "7D" (Table 2.1 – 2). Demand management, including parking supply and cost, is a sixth D, included in a few studies. While not part of the environment, demographics are the seventh D, controlled as confounding influences in travel studies (Ewing & Cervero, 2010).

Table 2.1 – 2 "D Measures"

"Ds"	Measures
Density	"Density is always measured as the variable of interest per unit of area. The area can be gross or net, and the variable of interest can be population, dwelling units, employment, building floor area, or something else. Population and employment are sometimes summed to compute an overall activity density per areal unit."
Diversity	"Diversity measures pertain to the number of different land uses in a given area and the degree to which they are represented in land area, floor area, or employment. Entropy measures of diversity, where small values indicate single-use environments and higher values more varied land uses, are widely used in travel studies. Jobs-to- housing or jobs-to-population ratios are less frequently used.
Design	Design includes street network characteristics within an area. Street systems vary from dense urban grids of highly interconnected, straight streets to sparse suburban networks of curving streets forming loops and lollipops. Measures include average block size, the proportion of four-way intersections, and number of intersections per square mile. Design is also occasionally measured as sidewalk coverage (share of block faces with sidewalks); average building setbacks; average street widths; or numbers of pedestrian crossings, street trees, or other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones.
Destination accessibility	Destination accessibility measures ease of access to trip attractions. It may be regional or local. In some studies, regional accessibility is a simply distance to the central business district. In others, it is the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral ones. The gravity model of trip attraction measures destination accessibility. Local accessibility is different, defined as distance from home to the closest store.
Distance to transit	Distance to transit is usually measured as an average of the shortest street routes from the residences or workplaces in an area to the nearest rail station or bus stop. Alternatively, it may be measured as transit route density, four distance between transit stops, or the number of stations per unit area.
Demand manage	Demand manage for cycling mainly refers to parking management, including the supply, price and regulation of parking facilities.

(Source: e.g. Ewing & Cervero, 2010; Litman, 2014)

In fact, comparing with physical built environment features, a number of studies agree with that demographic act as more important factors for cycling. Characteristics in both "6Ds" of built environment and demographic might have three possible directional influences on cycling: positive, negative, positive/negative (Zhao, 2014; Beenckers et al., 2012; Saelens et al., 2003; Winters et al., 2010; Fraser & Lock, 2011; Cervero & Duncan, 2003; Cervero et al., 2009; Moudon et al., 2005; Titze et al., 2008). The methodology of this study is a combination result of “Ds” model and social ecological framework, and six sorts of physical built environment features would be considered: 1) local density, 2) diversity of land use, 3) connectivity, 4) bike facilities, 5) green space, 6) job accessibility. This literature review will mainly focus on recent research (published after 2000) on the relationships between each sort of built environments and cycling (Table 2.1 – 3).

Table 2.1 – 3 Built environment attributes in literature

Citation	Study Area	Local density	Diversity of land use	Connectivity	Bike facilities	Green space	Job accessibility
Cervero & Duncan, 2003	San Francisco Bay Area	√	√	√	√	×	√
Saelens et al., 2003	/	√	√	√	√	√	×
Wendel-Vos et al., 2004	Maastricht, Netherlands.	×	×	×	×	√	×
Ewing et al., 2004	Gainesville, Florida	√	√	√	√	√	×
Schwanen et al., 2004	Netherlands:	√	×	×	×	×	×
Moudon et al., 2005	King County, Washington	×	√	√	√	√	×
Frank et al., 2005	Metropolitan Atlanta	√	√	√	×	×	×
Kerr et al., 2006	Seattle, King County	√	√	√	√	×	×
Titze et al., 2007	10 European countries	×	×	√	√	√	×
Dill & Voros, 2007	Portland region	×	×	√	√	×	×
Titze et al., 2008	Graz, Austria	×	√	×	√	×	×
Larsen et al., 2009	London, Ontario	√	√	√	×	√	×
Cervero et al., 2009	Bogota, Colombia	√	√	√	√	√	×
Winters et al., 2010	Vancouver, Canada	√	√	√	√	√	×
Fraser & Lock, 2011	/	√	√	√	√	√	×
Beenackers et al., 2012	Perth, Australia	√	√	√	√	√	×
Heesch et al., 2012	Queensland, Australia	×	×	√	√	√	×
Zhao, 2014	Beijing, China	√	√	√	√	×	×
Cui et al., 2014	Baltimore–Washington, Maryland	√	√	√	√	×	×

Collectively, there are several measures used in the literature to represent individual cycling behavior. These include 1) Proportions of bicycle used in a specify period (Zhao, 2014; Owen et al., 2010; Winters et al., 2010; Cervero & Duncan, 2003) which refers to the frequency of the cyclists to travel through cycling in comparison to other transport mode. 2) People who own bicycle trips during past week or past month are accounted as cyclists, and others are non-cyclists (Moudon et al., 2005; Titze et al., 2007&2008; Beenackers et al., 2012; Fraser & Lock, 2010; Cervero et al., 2009). 3) Cycling times in a specify period (Heesch et al., 2012; Saelens et al., 2003) refers to the number of tasks that are executed through commuting by riding a bike, which contains going to work, school or recreation on daily basis. Likewise, many cyclists like to do cycling without any need of commuting just to stay healthy and fit, which may be meaningful for policymakers to reconsider their bicycle transport plan.

2.2 Local density

A number of early evidences suggesting that residents from communities with high-density report higher rates of walking or cycling for the utilitarian purpose than low-density neighborhoods (e.g. Murakami & Young 1997; Saelens et al., 2003). To evaluate the impacts of density on travel behavior, it is important to specify whether it considers aggregated density (density and its associated land use factors, sometimes called compactness) or disaggregated density (density by itself, and other land use factors such as mix, street connectivity and parking supply considered separately) (Litman, 2014). Density itself is only a minor portion of the aggregated effects of other land use factors together. Similar to most studies that isolate density from these factors, in this review local density refers to the number of homes, people and jobs per unit of area, which can be measured at various scales: site, block, census tract, neighborhood, municipality, county, urban region or country (Cui et al., 2014; Litman, 2014).

Table 2.2 – 1 Impacts from local density on cycling in literature

Citation	Dependent variable	Independent variables	Estimated effects
Beenackers et al., 2012	Minutes of cycling transport and recreation, focus on the uptake of cycling	Residential density	+
Winters et al., 2010	Cycling frequency	Population density	+
Schwanen et al., 2004	Percentage of commuters using	Population density	+
Fraser & Lock 2011	Cycling frequency, school children	Population density	+
Saelens et al., 2003	The amount of walking/cycling trips per week	Population density	+
Cui et al., 2014	Daily bicycle ridership	Population density;	+
		household density	+
Zhao, 2014	Bicycle as transport mode	Population density	+
		Job-housing balance	-
		Employment density	+
Larsen et al., 2009	Children’s Cycling travel from school to home	Residential density	-
	Children’s Cycling travel from home to school		+
Titze et al., 2008	Non-cyclists and cyclists	Social support	+

From a broad perspective, the direct relationship between density and travel mode is still ambiguous. The effects of density on the use of the bicycle might often be indirect. Density may affect cycling because a higher density is related to higher destination accessibility (shorter distance) and higher levels of obstacles to car use (more traffic congestion and higher parking fees) (Litman, 2014). However, higher population or residential density is found to relate to higher cycling rates and lower car use (Table 2.2 – 1). In Zhao’s study of Beijing (2014), population density (point elasticity = 0.0034) and employment density (point elasticity = 0.1265) show positive influence on mode choice as bicycle, but job-housing balance index (point elasticity = -0.4911) is powerful negatively related to cycling. From this result, he summarized that local density has no significant effects on the use of a bicycle for commuting in Beijing. This situation is different from almost all western cities. A particular example is that a case study in Metro Vancouver shows that higher population density will increase odds of bicycling (Winters et al., 2010). Additionally, a Residential Environment Project in Perth (Western Australia) identifies that after residential relocation, the uptake of transport-related cycling is determined by an increase in objective residential density (OR = 1.54, 95% CI = 1.04, 2.26) (Beenackers et al., 2012). Obviously, a subdivision of factors that represent local density is useful for research in this field.

Furthermore, empirical studies reveal that the similar environment characteristics may generate different influences on different people, such as schoolchildren, unemployed or retired (Forsyth et al., 2009). Fraser & Lock (2011) addressed the importance of residential density on school children, according to a systematic review of the effect of the environment on cycling based on previous studies in several western countries. For Californian school children, high neighborhood population density is correlated with cycling and working. Moreover, in Larsen's study (2009), a mid-sized Canadian city (London, Ontario), we find that environmental influences on children's mode choice for transport between from school to home and from home to school are distinguishment. In detail, cycling travel from school to home is positively associated with lower residential densities, but when it comes to active travel from home to school, higher residential densities is positively related to mode choice as bicycle (Larsen et al., 2009). To investigate how local density affect cycling, it is also necessary to distinguish between origins and destinations.

The impacts of different types of housing units still need to conduct further research. For example, Titze's et al. (2007) reveals that social support was positively related to cycling for transport. That indicated that multi-family buildings provided a supportive social environment (support from friends or family members as well as observing others bicycling) be potential determinants of active mobility and should be considered when designing interventions. The type and area of housing unit might also lead to the issue of bicycle parking security. Bicycle parking requirements for single family and multi-family are different. Thus, improving bicycle parking security may increase the usage of this transport mode (Titze et al., 2007).

2.3 Diversity of Land use

Historically, Mitchell & Rapkin's *1954 Urban Traffic: A Function of Land Use* firstly articulated the connection between land use diversity and travel patterns. However, the idea that land use and design policies could be used to influence travel behavior was not widely explored until the mid-1980s, when physical, financial, and environmental constraints began to limit additional roadway expansions (Handy et al., 2002). Commonly, "Land use" refers to the distribution of activities across space, including the location and density of different activities. These activities could be grouped into relatively coarse categories, such as residential, commercial, office, industrial, and other activities (Rodrigue, 2013). "Diversity of land use" refers to locating different types of land uses close together (Rodrigue, 2013). This factor could be measured by entropy indices (the variety of different uses in a neighborhood) or dissimilarity indices (the number of adjacent parcels with different uses) (Handy et al., 2002; Litman, 2014). Both methods result in scores from 0 to 1.0. Ewing & Cervero et al. (2010) argued that another method known as jobs-to-housing ratios were not usually considered to date.

Table 2.3 – 1 Impacts from diversity of land use on cycling in literature

Citation	Dependent variable	Independent variables	Estimated effects
Frank et al., 2005	Minutes of moderate activity per day	land-use mix	+
Cui et al., 2014	Number of bicycle trips generated by a given analysis zone per day	Number of retail or recreational locations	+
Moudon et al., 2005	Cyclists and non-cyclists	"Clusters" of offices, hospitals and fast food restaurants	+
Winters et al., 2010	The likelihood that a trip was made by bicycle	Agglomeration of commercial land use, industrial land use, educational land use and closest sports facility	+
Zhao, 2014	Bicycle as transport mode	Diversity of land use	+
Kerr et al., 2006	Weight cycling or walking scores for schoolchildren	Diversity of land use	+
Ewing et al., 2004	Bicycle as transport mode for travel to school	Diversity of land use	-
Larsen et al., 2009	Cycling mode choice from school to home	Diversity of land use	Insignificant
	Cycling mode choice from home to school		+
Cervero & Duncan, 2003	Bicycle as transport mode	Diversity of land use	+

Mixed land-use can increase cycling levels (Table 2.3 – 1). Improving the diversity of land use may generate a higher likelihood of cycling among ordinary people (Krizek & Levinson, 2005; Buehler & Pucher, 2010; Mcclintock, 2002; Pucher & Buehler, 2008; Pucher et al., 2010; Saelens et al., 2003). One reason might be that increased mix would reduce travel distances and allow more walking and cycling trips (Litman, 2014; Owen et al., 2010). Moreover, Titze et al. (2008) hypothesized that destination activities, such as the variety of shops or other services, rather than mixture along the route appeared to be the dominant factors for cycling.

When taking a closer look at land use patterns by land use category, a considerable number of studies consistently reveal that with the number of transit stations, grocery stores, and retail stores increasing in neighborhoods, people tend to rely on non-automobile modes more frequently (Giles-Corti & Donovan, 2003; Handy & Clifton, 2001; McConville et al., 2011; Ortúzar et al., 2000). In the study of exploring how land use relate to bicycle ridership in the State of Maryland, Cui et al. (2014) found that, the number of shops and the number of recreational locations had positive influences on aggregating more bike trips in a distinct zone. This finding suggested that if urban development provided more opportunities for discretionary activities, as locating shopping and recreational centers, would improve local cycling levels to some extent in certain areas (Cui et al., 2014). Furthermore, in urbanized King County, Washington, the presence of “Clusters” of offices, hospitals, and fast food restaurants is positively associated with the odds of cycling (Moudon, 2005). Similarity, Winters’ study (2010) found that the agglomeration of commercial land use, industrial land use, educational land use and closest sports facility shows positive impacts on cycling for residents.

Several empirical studies also focus on analyzing the impacts of land use diversity on people with different social environment attributes. In the case study of Beijing, for work trips, Zhao (2014) proved that the diversity of land use had significant effects on the use of bicycle. Interestingly, according to modal (mean) point elasticity analysis, Zhao (2014) found that the elasticity of diversity of land use equaled to 0.3012, which was the third-most-powerful factor influencing bicycle commuting among all significant built environment variables. From utilitarian purposes, higher diversity of land use will increase the number of potential nearby cycling destinations. However, the relationship between land use mix and children’s travel is still less clear. With data from Gainesville in Florida, Ewing et al. (2004) found a negative correlation between land use mix and non-motorized travel to school, but Kerr et al. (2006) found the opposite. Then, Larsen et al. (2009) put forward that the likelihood of cycling to school was positively associated with higher land use mix, however, diversity of land use did not act as a significant predictor for children’s trips from school to home. Furthermore, Larsen et al. (2009) mentioned that diversity of land use might be a proxy for other environmental or social factors because its impacts on active travel were still not as precise for youths as for adults and need further research.

Cervero & Duncan et al. (2003) mentioned *"travel choices depend as much, if not more, on the degree of land-use mixing as urban densities. Among built environment features, urban design and land-use diversity were positively associated with the decision to ride a bicycle"*. From a comprehensive perspective, there is a higher likelihood of cycling by improving the diversity of land use (Zhao, 2014; Cervero et al., 2003; Saelens et al, 2003; Winters et al., 2010). Mostly, diversity of land use is controlled by zoning ordinance, which may always reflect political decision-making at the local level through urban design (Saelens et al., 2003).

2.4 Connectivity of road network

Connectivity has been found to have significant effects on travel mode choice as cycling (Table 2.4 – 1). In general, connectivity represents the directness of travel between two points - origin and destination, which is directly related to the characteristics of street design (Saelens et al., 2003; Owen et al., 2010; Handy et al., 2002; Litman, 2014; Ewing & Cervero, 2010). Recently, Litman et al. (2014) described a situation that poorly connected road network with many dead-end streets that connect to a few major arterials provided less accessibility than a well-connected network. Increasing connectivity may reduce vehicle travel by reducing travel distances between origins and destinations, because paths provide shortcuts, thus, cycling are more directly than driving (Litman, 2014). In policy aspect, street connectivity ordinances that ensure more direct routes between residential and commercial areas (Handy et al., 2005).

Table 2.4 – 1 Impacts from connectivity of road network on cycling in literature

Citation	Dependent variable	Independent variables	Estimated effects
Cui et al., 2014	Number of bicycle trips generated by a given analysis zone per day	Average freeway distance	-
		Transit accessibility	+
		Average congestion speed	-
		Average free flow speed	-
Winters et al., 2010	the likelihood that a trip was made by bicycle	Intersection density	+
		Percentage of highway	-
		Percentage of arterial	-
Zhao, 2014	Bicycle as transport mode	Density of local streets	+
		Intersection density	+
Dill & Voros, 2007	Non-cyclist, irregular cyclist and regular year-round cyclist	Street connectivity	+
Beenackers et al., 2012	Cyclist and non-cyclist	Street connectivity	+
Larsen et al., 2009	Cycling mode choice from school to home	Intersection density	+
	Cycling mode choice from home to school		Insignificant
Moudon et al., 2005	Cyclist and non-cyclist	Street connectivity	Insignificant
Cervero et al., 2009	Cycling for utilitarian (cycled or not)	Street density	Insignificant

To date, several methods are frequently used to reflect the connectivity of road network. Handy et al. (2002) summarized three measures: 1) intersections per square mile of area, 2) ratio of straight-line distance of network distance, 3) average block length or road length (Handy et al., 2002; Winters et al., 2010; Ewing & Cervero, 2010). Road connectivity is a proxy for urban design in street or neighborhoods level. Street networks vary from dense urban grids of highly interconnected, straight streets to sparse suburban networks of curving streets creating circulation. Occasionally, street design could also be measured as sidewalk coverage (share of block faces with sidewalks); average building setbacks; average street widths; or numbers of pedestrian crossings, street trees, or other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones (Ewing & Cervero, 2010). Several non-mainstream measures for road network also cannot be ignored. Road network as highway and main road length are playing important roles in motor trips, however, their adverse impacts are significant when it comes to cycling trips (Zhao, 2014; Winters et al., 2010). Pikora et al. (2003) addressed that two critical factors were held to influence cycling as a mode of transportation. The first was the presence of a continuous route, with few intersections and places where cyclists must stop. The second concerned traffic safety and included speed and volume of the traffic. Traffic hazards related factors are unambiguously regarded as negative Factors (Cervero et al., 2009; Beenackers et al., 2012; Titze et al., 2008; Fraser & Lock, 2011).

Moreover, the connection between the built environment and pedestrian behavior might be more a matter of residential location choice than of travel choice (e.g. Cao, 2006). Similarity, Beenacker et al. (2012) found that after relocation, 5% of the non-cyclists took up transport-related cycling, and 7% took up recreational cycling. Street connectivity acted as a determinant for commencing recreational cycling (Beenacker et al., 2012). When taking a closer observation, one finds unexpected results for street connectivity. Moudon et al. (2005) pointed that road connectivity, captured as block size presented as an insignificant factor for cycling in urbanized King County, Washington, which might be downplayed because of the limited bicycle transport infrastructure in study area.

Transit accessibility is highly related to the road network in an urban system. Also, transit proximity or accessibility should affect transport mode selection. In Zhao's study (2014), closer proximity to public transport facilities tends to decrease rather than increase the use of the bicycle as a major mode for commuting. Zhao et al. (2014) reasoned that proximity to public transport had a substitutive effect with respect to the bicycle in Beijing, where public transit charges are low and subsidized by the government. However, the situation of this study area is distinguishment. From a US perspective, Moudon et al. (2005)

found that people living near trails were more likely to bicycle than drive to the trail. The significance of proximity to trail in Moudon's research (2005) strongly suggested that adding continuous and protected facilities near residential areas, and securing neighborhood access to them could increase residential cycling frequency.

2.5 Bicycle lanes and bicycle facilities

It seems that among six groups of physical built environment features, bicycle facilities have the most directly positive influences on cycling. Bike lanes and bicycle friendly routes always have more bicycle facilities than other road conditions (Zhao, 2014; Cervero et al., 2009; Titze et al., 2008; Moudon et al., 2005; Beenackers et al., 2012; Fraser & Lock, 2011). Moudon et al. (2005) found that impacts from bike lanes on cycling might be insignificant in the situation of limited bicycle transportation infrastructure were existing. For cyclists, time spent cycling in mixed traffic is more onerous than time spent cycling on bike paths (Hunt & Abraham, 2006). Also, proximity to bike lanes is positively associated with non-motorized transports (Cervero et al., 2009). State and local agencies are advised to build designated bicycle paths based on traffic conditions and increase bicycle parking capacity by particular establishments (Cui et al., 2014).

Table 2.5 – 1 Impacts from bicycle lanes and bicycle facilities on cycling in literature

Citation	Dependent variable	Independent variables	Estimated effects
Heesch et al., 2012	Cyclist and non-cyclist among women	Designed bike lanes	+
Winters et al., 2010	the likelihood that a trip was made by bicycle	Designated bike route	+
		Off-street path	+
		Traffic calming features	+
		Markings of signage for cyclists	+
		Crossings with traffic lights	+
Zhao, 2014	Bicycle as transport mode	Presence of bicycle lanes	+
Dill & Voros, 2007	Non-cyclist, irregular cyclist and regular year-round cyclist	Miles of bike lanes	+
	Cyclist and non-cyclist for transport	Bicycle route length	Insignificant

Beenackers et al., 2012	Cyclist and non-cyclist for recreation		+
Larsen et al., 2009	Cycling mode choice for schoolchildren	Sidewalk length	Insignificant
Moudon et al., 2005	Cyclist and non-cyclist	Presence of bicycle lane	+
Cervero et al., 2009	Cycling for utilitarian (cycled or not)	proximity to bike lanes	+

The bike path will increase the number of cycling trips (Table 2.5 – 1). However, that is infrequently evaluated when it comes to transport choice (Saelens et al., 2003). Owen et al. (2010) proved the significant influences from bike lane connectivity on cycling for transport. Moreover, in the study of Beijing, Zhao (2014) found that the odds of an employed-adult choosing to cycle for transport will increase when the length of bicycle land in the neighborhood increases. But the elasticity of bike lane (+0.1909) is smaller than the diversity of land use (+0.3012), which implies that the most effective way of encouraging cycling would be to combine improvements in bicycle facilities with urban environment elements (Zhao, 2014).

In the research of how bike lanes affect cycling, some other issues also should be addressed. Firstly, with respect to research objective, Fraser & Lock (2010) summarized that the majority of empirical studies did not specify the impact of bike paths as a primary objective, but included them into a broader estimations of urban environments. Secondly, with respect to non-motorized transport purpose, a comparison study on cycle for transport and cycle for recreation after residential relocation finds that the availability of bicycle route will encourage residents to cycle for recreation (Beenackers et al., 2012). Thirdly, with respect to gender differences, for the sake of traffic safety, female cyclists are more rely on the usage of bike lanes (Heesch et al., 2012).

2.6 Green Space

Park is an essential element for complete communities (also called the urban village). A compact walkable neighborhood center should contain commonly used services and activities, in which the function of parks or green space cannot be overlooked (Litman, 2014).

In the late 1990s, scholars mentioned that access to parks was gradually becoming a significant influential factor for individuals choosing a residence (Levinson, 1998). Handy et al. (2002) addressed built environment affected physical activity from six dimensions: 1) Density and intensity, 2) Land use mix, 3) street connectivity, 4) street scale, 5) aesthetic qualities, 6) regional structure. In the proposed social ecological model, for objective environmental factors and physical activity, the presence of parks and open space for recreation are included in aesthetic features (Pikora et al., 2003; Saelens et al., 2003). From another aspect, in the study of San Francisco Bay Area, Cervero & Duncan (2003) found that for trip characteristics, the existence of recreation or entertainment was positively correlated with mode choice as bicycle. In addition, Titze et al. (2008) put forward that the attractiveness of cycling conditions should be considered together with traffic safety issues.

Table 2.6 – 1 Impacts from green space on cycling in literature

Citation	Dependent variable	Independent variables	Estimated effects
Cervero & Duncan, 2003	Bicycle as transport mode	the existence of recreation	+
Wendel-Vos et al., 2004	Cycling trips for transport	The area of parks	+
Moudon et al., 2005	Cyclists and non-cyclists	the presence of parks	Insignificant
Winters et al., 2010	The likelihood that a trip was made by bicycle	Percentage of land use as parks	+
Titze et al., 2007	Non-cyclist, irregular cyclist and regular cyclist	Green area	Insignificant
		high emotional satisfaction	+
Heesch et al., 2012	Recreation Cycling frequency	bush paths	+
Beenacker et al.,2012	Cyclist and non-cyclist for transport	Access to parks	+
		Recreation destinations	+

	Cyclist and non-cyclist for recreation	Access to parks	Insignificant
		Recreation destinations	

Several studies claimed statistically significant associations between green or open space and cycling (Table 2.6 - 1). To investigate how green space affect cycling, it is necessary to separate recreation or exercise-related cycling from transport-related cycling (Pikora et al., 2003; Saelens et al., 2003; Moudon et al., 2005). For example, Moudon et al. (2005) failed to prove significance when objectively measured the presence of parks because his study was lack of a distinguishment from transport-related cycling and recreation-related cycling. Recently, several studies have conducted separately research on different cycling purposes, which assist to improve the understanding of the associations between cycling behavior, and objective built environment attributes. Some of them addressed the importance of green space on recreational cycling behavior (Hunt & Abraham, 2006; Heesch et al., 2012; Beenacker et al., 2012). Beenacker et al. (2012) found that the uptake of transport-related cycling was determined by better access to parks (OR=2.60, 95%CI=1.58, 4.27) and larger number of recreation destinations (OR=1.57, 95%CI=1.12, 2.22). Undoubtedly, the enjoyment of cycling is positively correlated with regular cycling (e.g. Titze et al., 2007).

2.7 Job Accessibility

A few number of studies used job-housing balance index to represent the ratio between the number of jobs and residents (Zhao, 2014). However, most studies ignore to analyze the correlations between bicycle usage and job accessibility. Especially for adults, going to the workplace should be an important composition of transport purpose cycling behavior. Also, Job accessibility should be highly correlated with destination accessibility (e.g. Cervero et al., 1995). In a California case study, Cervero & Duncan (2003) found that within a larger 5-mile radius of a trip origin, higher overall employment densities (as reflected by the employment accessibility variable; employment accessibility was presented as number of jobs within 5 miles of origin) might deter transport mode choice as bicycle. Presumably this is because dense employment settings, like urban job centers and edge cities, often create numerous roadway conflict points and safety hazards for bicyclists (Cervero & Duncan, 2003). Literature seldom regards job accessibility in a larger area (from 5 miles to 50 miles) as a significant predictor of adults' cycling behaviors.

2.8 Research Hypotheses

H1: Local density, diversity of land use, road connectivity and bike route length related index will generate positive influences on cycling behaviors.

H2: Green space and job accessibility are significant predictors for cycling behaviors, together with local density, diversity of land use, road connectivity, and bike route length.

H3: The impacts of built environment attributes to individual cycling behavior will also be affected by personal social characteristics, such as students, employed and unemployed.

H4: The effects of built environment attributes on cycling activity at destinations (school/workplace) are distinguished from at origins (home).

CHAPTER 3

METHODOLOGY

3.1 Study Area

The area for study is urbanized California, including nine counties of the San Francisco Bay Area, six counties of the Sacramento area (SACOG), eight counties of the San Joaquin Valley, six Southern California Association of Government (SCAG's) counties, and San Diego County (Figure 3.1). In this study area, personal- and household-level information from 2010-2012 California Household Travel Survey (CHTS) and 2009 National Household Travel Survey (NHTS) are linked with built environment attributes by location. These locations are then buffered by a quarter mile, half mile, and full mile radii to create circular areas. Built environment characteristics in these circular are recorded.

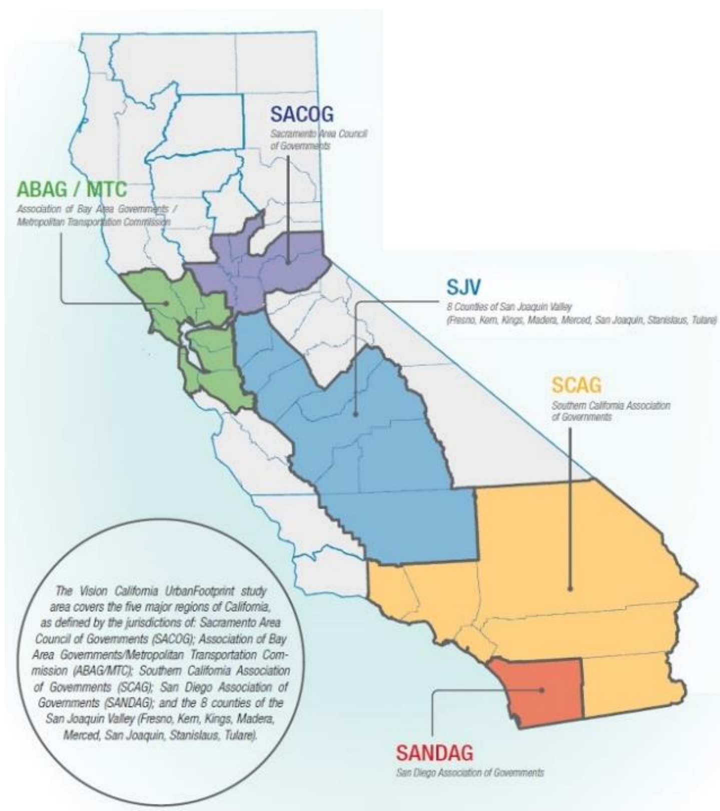

Figure 3.1 Study Area (Source: *UrbanFootprint Technical Summary – Vision California – July 2012*)

3.2 Data Measures

3.2.1 Built environment measures

In 2010-2012 CHTS, units in structure are described as following groups: *1) Single family house not attach, 2) Single family house attached, 3) A mobile home, 4) Building with 2 to 4 layers, 5) Building with 5 to 19 layers, 6) Building with more than 20 layers, 7) Boat van*. However, this study used two variables as single-family homes and multiple-family homes. Single-family homes refer to Single family house not attach, single family house attached and mobile home. Multiple-family homes refer to Building with 2 to 4 layers, building with 5 to 19 layers and building with more than 20 layers.

Others built environment characteristics are collected from *Vision California (UrbanFootprint) Base Grid Variables, July 2012*. Residential density measures as a ratio that the number of residents divided by the area of a particular radius. Employment density is calculated by the same method as residential density. Both are used to represent local density.

The diversity of land use at the community level for travel behavior studies is often represented by an entropy index (e.g. Salon, 2014; Zhao, 2014). This index is usually based on the square footage of buildings in the neighborhood that is used for different purposes and is commonly calculated as:

$$Physical\ land\ Use\ Mix = \sum_{i=1}^{N} \frac{p_i * \ln(p_i)}{\ln(N)}$$

where pi is the proportion of the total square footage in the area with land use i. Our physical land use mix index represents mixing of 3 categories in specific radii: considered urban, considered greenfield and considered constrained development areas.

That leads to a physical land use mix variable that ranges from 0 to 1. The value of 0 shows that a grid cell has only one land use. The higher the value of physical land use mix variable, the greater the diversity of physical land use (Zhao, 2014).

Because this study analyzes neighborhoods statewide, data limitations made it impossible for us to create a square footage based representation of land use mix from a functional aspect. As a closely-related proxy, this study uses an “activity mix” variable, calculated using the same method as “physical land use mix”.

$$Activity\ Mix = \sum_{i=1}^{N} \frac{p_i * \ln(p_i)}{\ln(N)}$$

where pi is the proportion of people (residents + employees) engaged in activity i in specific radii. In particular, our activity mix variable represents mixing of 16 categories in each buffer: residential population, and the number of jobs in each of 15 categories – retail jobs, restaurant and accommodations jobs, entertainment and recreation jobs, office jobs, education jobs, medical and social services jobs, public jobs, manufacturing jobs, transportation and warehousing jobs, utilities jobs, wholesaling jobs, construction jobs, agricultural jobs, extraction industry jobs, and other jobs. We assume that the activity mix index should be highly correlated with functional land use mix index. Moreover, physical land use mix and activity mix present land use mix from two different perspectives, so both of them are meaningful for our research.

In each particular radius, road length, bike friendly road length and bike route length are directly recorded as their measurements based on the unit of meters. Also, the number of street intersections and parks are directly recorded. Moreover, each park area is directly measured as the total park area based on the unit of square-meter in given buffer. The job accessibility indices are calculated by following formulation:

$$Gravity\ Job\ Accessibility = \frac{\sum_{j} E_{j}}{d_{ij}}$$

Where Ej represents the total number of available jobs in a specific zone (5 miles radii or between 5 miles to 50 miles radii). d shows the distances between zonal centroids, for all i-j interzonal pairs that are less than 50 miles (e.g. Cervero et al., 1995).

3.2.2 Demographic variables and characteristics

In the existing literature, socio-demographic factors are commonly regarded as explanatory variables for analyzing the relationship between built environment attributes and travel behaviors. The significant impacts of social environment attributes to travel behavior have been addressed many times. The 2010-2012 California Household Travel Survey (CHTS) provides data on cycling trips, together with individual socio-economic characteristics. The 2010-2012 sample includes information on a total of nearly 105,000 respondents over four years of age. The results here focus on those individuals who were surveyed on a weekday, provided sufficient information for analysis. Outliers were identified as any person who reported no cycling trip in the past week. To check the robustness of the results, we added into another dataset – the California portion of the 2009 National Household Travel Survey (NHTS) to generate demographic variables and cycling dependent variable to make a comparison. Weights do not appear in our statistical analysis of the determinants of cycling times in one week.

The used socio-demographic factors consist of gender, age, race, education level, household size, home ownership, number of household bicycles, household vehicles available, household incomes and household life cycle. With respect to categorical variables, gender, race, home ownership related variables are coded with dummy binary variables (0 or 1) to describe two different situations. The household life cycle has eight different conditions, but this sort of factors are still treated as categorical variables (from 1 to 8). Distinct interval values label other continuous variables, and then recorded as new variables. The results are as following (Table 3.2.2 – 1):

Table 3.2.2 – 1 Demographic characteristics coding

Categorical variables		Code
Gender	Male	1
	Female	0
Race1	Hispanic	1
	Non-Hispanic	0
Race2	White but non-Hispanic	1
	Non-white, and white-Hispanic	0
Homeownership	Homeowner	1
	Rent	0
Education level	not high school graduated or less	1
	high school graduates	2
	with some college credit but no degree	3
	with associate or technical school degree	4
	hold bachelor's or undergraduate degree	5
	hold graduated degree	6
Household life cycle	one adult, 18-64, no children	1
	2+ adults, at least one adult 18-64, no children	2
	one adult, youngest child 0-5	3
	2+ adults, youngest child 0-5	4
	one adult, youngest child 6-17	5
	2+ adults, youngest child 6-17	6
	one adult, over 64, no children	7
	2+ adults, all adults over 64, no children	8
Continuous variables		
Age1 – children	5 to 12 years	1
	13 to 17 years	2
Age2 – adults	18 to 34 years	1
	35 to 44 years	2
	45 to 54 years	3
	55 to 64 years	4
	64 years and over	5

Household size	1-person household	1
	2-person household	2
	3-person household	3
	4-or-more-person household	4
Household vehicles available	No vehicle available	1
	1 vehicle available	2
	2 vehicle available	3
	3 or more vehicles available	4
Number of household bicycles	One household bicycle	1
	Two household bicycles	2
	Three or more household bicycles	3
Annual household incomes	Incomes less than $25,000	1
	Incomes $25,000 -$50,000	2
	Incomes $50,000 - $100,000	3
	Incomes more than $100,000	4

The number of valid samples in 2010-2012 CHTS reaches 51,485, while, 2010 California Census Summary contains total 37,253,956 persons' information. One of the most significant characteristics of this study is that all samples are bicycle owners. 49.7 percent of all individuals in census summary are male, and proportion of male in Travel Survey is 0.5 percent higher than that of census summary. A seven-level age variables (child: 5-12 years, 13-17 years; adult: 18-34 years, 35-44 years, 45-54 years, 55-64 years and 65 or more than 65 years) was handling participant age in this study. With respect to census summary, the group of 18 to 34 years owns a larger percentage than other age groups, which equals to 24.8 percent. Comparing the fractions of seven age groups in Travel Survey, 45 to 54 years and 55 to 64 years are larger than other age groups. Obviously, one feature of these samples used in this research is that the average age is greater than that of census summary (Figure 3.2.2 – 1). In addition, it is necessary for us to make more detail explanations for three cutoffs in our study. The cutoff five years was selected to correspond roughly with an age of inability because children less than five years old are not strong enough to ride a bicycle. The cutoff 13 years was applied to distinct adolescent or schoolchildren from young children. The cutoff 65 years means the elderly might be unemployed or retired.

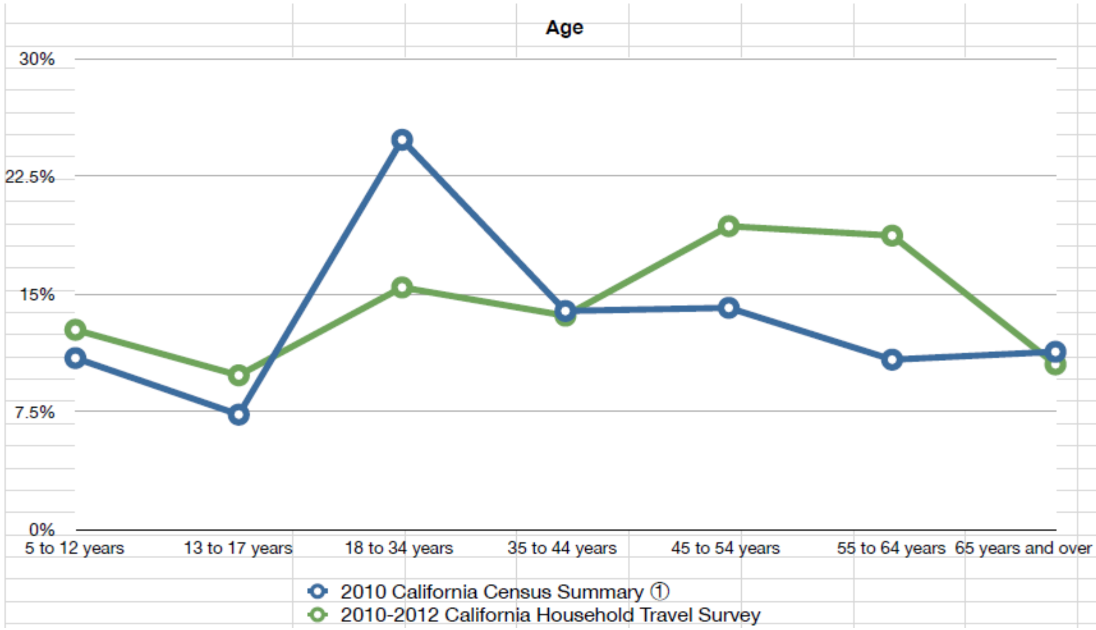

Figure 3.2.2 – 1 Comparison of Age between 2010 California Census summary and 2010 – 2012 CHTS

Previous studies supported the importance of education level to physical activity, such as walking and bicycling. Therefore, most of them controlled this personal attribute for quantifying research in this study area. Moreover, their findings indicated that participants with higher education were more likely to cycle than others (Titze et al., 2008; Owen et al., 2010; Winter et al., 2010; Handy et al., 2005; Bruijn et al., 2005; Forsyth et al., 2007; Heesch et al., 2012; Cervero et al., 2009; Beenackers et al., 2012). Titze et al. (2008) and Winter et al. (2010) gave out detailed methods to classify and explain education attainment for interviewees. The method used in study to reclassify education attainment for samples is aligning with these existing research, as 1) not high school graduated or less, 2) high school graduates, 3) with some college credit but no degree, 4) with associate or technical school degree, 5) hold bachelor's or undergraduate degree, 6) hold graduated degree. In 2010 – 2012 CHTS, 27.5 percent of participants are not high school graduated or less, which is the largest education level group. However, in census summary, 22.2 percent are with some college credit but no degree. To the education level of high graduates, travel survey is 6.8 percent less than that of census summary. Also, to the group of with some college credit but no degree, travel survey is 8.9 percent less than that of census summary. All other four education-level samples have larger proportions in travel survey than that in census summary. In short, travel survey contains more people with higher education level and more people with lower education level (Figure 3.2.2 – 2).

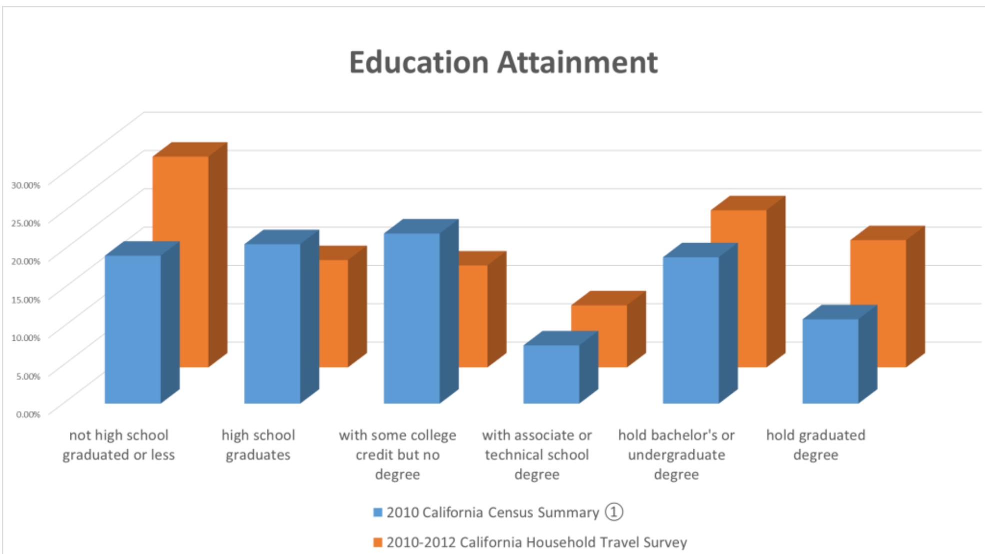

Figure 3.2.2 – 2 Comparison of Education Attainment between 2010 California Census summary and 2010 – 2012 CHTS

Different races may have different physical activity behaviors (Forsyth et al., 2007; Saelens et al., 2003). A general method is coding different races as white or non-white (e.g. Forsyth et al., 2009; Moudon et al., 2005) because whites are always less physically active. However, in recent years, Latinos has surpassed white as the largest racial group in California (Lopez, 2014). Therefore, this study divided participants into three groups as 1) Hispanic, 2) White but not Hispanic, 3) some other races (include two or more races). The majority is white but non-Hispanic Caucasian in travel survey, which equals to 62.0 percent. The proportions of this ethnicity group in census summary are 40.1 percent (Figure 3.2.2 – 3).

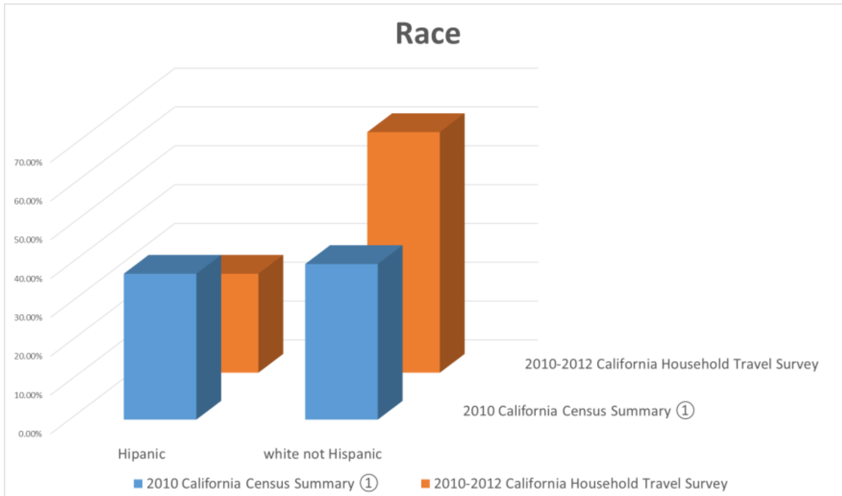

Figure 3.2.2 – 3 Comparison of Race between 2010 California Census summary and 2010 – 2012 CHTS

In 2010-2012 CHTS, the range of household sizes covers from 1 to 15 household members. On the other hand, from 2010 California Census, total 13,682,976 households are divided into seven groups from 1-person household to 6-person household and end up with 7-or-more-person household. The mean value of household size in travel survey is 2.96, which is approximately equal to that of census summary (equals to 2.9). A slight distinct in two databases is that 1-person household is accounted for 23.3 percent in Census summary, and that of travel survey drops 10.3 percent (Figure 3.2.2 – 4). Household size in travel survey could be seen as a representative feature. In order to make the data distribution more reasonable and representative, this study classifies household size into four groups as 1) 1-person household, 2) 2-person household, 3) 3-person household and 4) 4-or-more-person household. Titze et al. (2008) indicated that social support will generate positive impacts on cycling for transport. That suggests that people from larger household size homes could receive more encourage or support from their friends or other family members, as well as more possibilities to observe others bicycling.

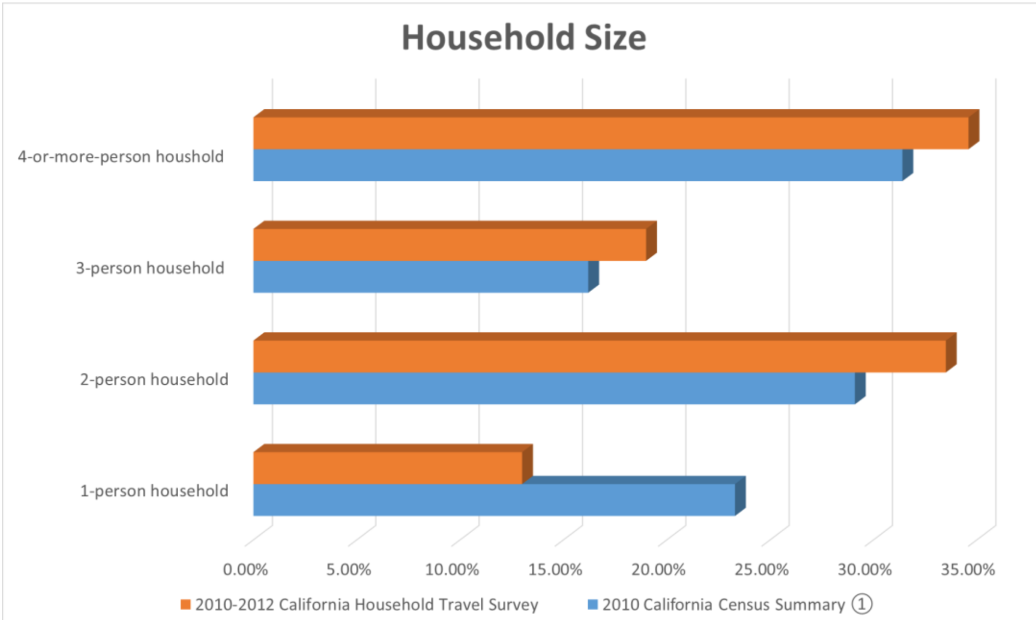

Figure 3.2.2 – 4 Comparison of Household size between 2010 California Census summary and 2010 – 2012 CHTS

With respect to home ownership, in census summary 55.6 percent of Caucasian are from homeowner family. In travel survey, that number reached 80.9 percent. This is a difference that cannot be neglected. Both available household vehicles and number of household bicycles seem will cause directional influence on household members' cycling behavior. Individuals from households with few available vehicles may be more likely to cycling for transport purposes than enough available household vehicles individuals. Also, people from households with few bicycles may be less likely than other to cycle for transport. This study codes vehicle available attributes into four groups as 1) No vehicles available, 2) one vehicle available, 3) two vehicles available, 4) 3 or more vehicles available. In both travel survey and census summary, two car available owns a larger proportion than other groups. For travel survey that proportion equals to 48.7 percent, which is 11.3 percent higher than that of census summary. When it comes to the feature as one vehicle available, travel survey has a proportion of 22.2 percent, which is 10.0 percent lower than that of census summary. The mean values of household vehicle available are nearly the same in both two databases (Figure 3.2.2 – 5). While, the number of household bicycles is not included in 2010 California Census. Based on travel survey data, this study classifies data of number of household bicycles into three groups as 1) one household bicycle, 2) two household bicycles, 3) Three or more household bicycles. In addition, three groups are nearly uniform distribution.

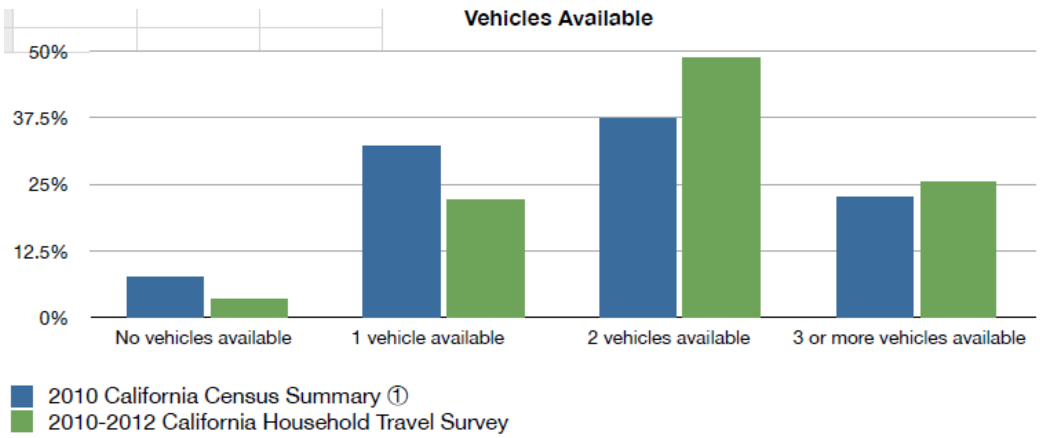

Figure 3.2.2 – 5 Comparison of Vehicles available between 2010 California Census summary and 2010 – 2012 CHTS

Household incomes, which could be seen as the most important factor to classify different types of people, is highly correlated with local density indices. In the 1995 Nationwide Personal Transportation Survey (1995 NPTS), low-income households were disproportionately likely to reside in high-density urban areas, and that they were much more likely to do non-motorized transport than their higher-income counterparts (Murakami & Young, 1997). Seemly, built environment should not be a causal factor itself, but rather act as a proxy for a set of socio-economic factors that do affect travel behavior

(Handy et al., 2005). To represent annual household incomes, this study classifies household incomes background for each interviewee as 1) annual incomes less than $25,000, 2) annual incomes $25,000 -$50,000, 3) annual incomes $50,000 - $100,000, 4) annual incomes more than $100,000. Comparing with census summary, samples in travel survey have more annual household incomes (Figure 3.2.2 – 6).

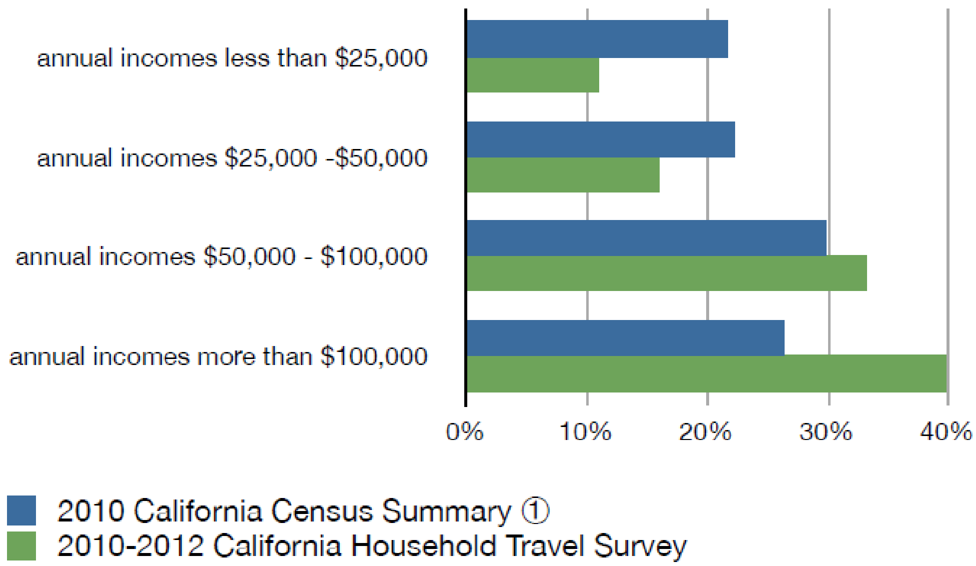

Figure 3.2.2 – 6 Comparison of Annual Household incomes between 2010 California Census summary and 2010 – 2012 CHTS

For representing life cycle stage, this study divides households into eight possible life cycle categories as previous research, listed and described in Table 3.2.2 – 2 (Salon, 2014). As is evident from the table, it is difficult to obtain a perfect match between census summary definition and what we could put together from the 2010-2012 CHTS. Specifically, Salon et al. (2014) pointed out that there were two census definitions were unable to match (Table 3.2.2 – 2). Firstly, the census only lists related children in a household, while the travel survey includes all members living in a household regardless of relationship. Similarity, this study does not expect this to be a large difference since almost all children who are under 18 years of age live with relatives. Secondly, the census references all households to the age of the "householder" – defined as the person who is responsible for paying the housing costs – while the travel surveys reference all family members to the person who identifies as "self" when answering the survey. That may or may not be the same person in a given household. However, this difference is meaningful only in differentiating between life stages 2 and 8, so we do not expect that it would have a large effect on our summary statistics tables (Salon, 2014). After classification, two groups show significant differences between census summary and travel survey. 1) One adult, 18 – 64, no children shows 11.6 percent drop in travel survey from 21.5 percent of census summary. 2) 2+ adults, youngest child 6-17 is taken up 25.7 percent of travel survey, which is 13.6 percent higher than that of census summary (Figure 3.2.2 – 7).

Table 3.2.2 – 2 Comparison of definitions of household life stage between 2010 California Census summary and 2010 – 2012 CHTS

Life Stage Code	Census Definition	Travel Survey Definition
1	one adult, 18-64, no children	one adult, 18-64, no children
2	2+ adults, householder 18-64, no children	2+ adults, at least one adult 18-64, no children
3	one adult, youngest related child 0-5	one adult, youngest child 0-5
4	2+ adults, youngest related child 0-5	2+ adults, youngest child 0-5
5	one adult, youngest related child 6-17	one adult, youngest child 6-17
6	2+ adults, youngest related child 6-17	2+ adults, youngest child 6-17
7	one adult, over 64, no children	one adult, over 64, no children
8	2+ adults, householder over 64, no children	2+ adults, all adults over 64, no children

(*Source: Salon, Final Report Quantifying the effect of local government actions on VMT 2014*)

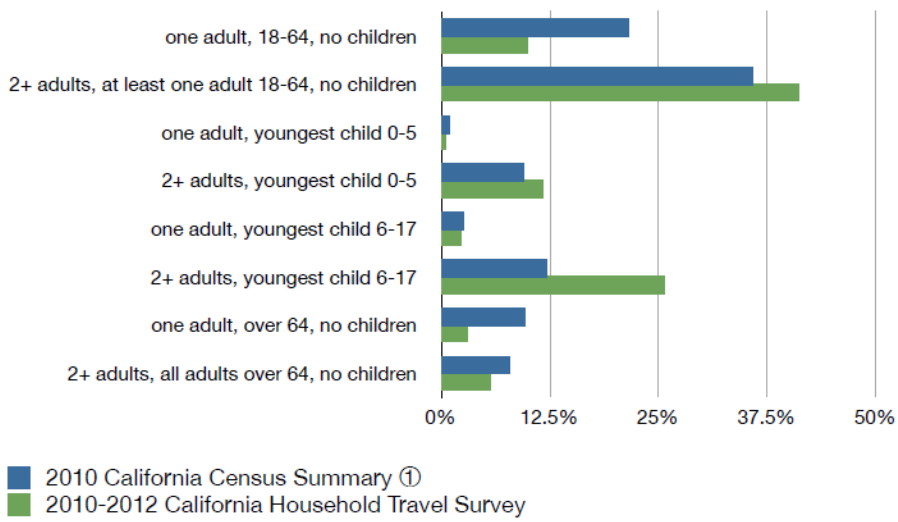

Figure 3.2.2 – 7 Comparison of Household life stage between 2010 California Census summary and 2010 – 2012 CHTS

Generally speaking, personal attributes data used in this study have following characteristics: 1) more elderly and children are contained, which leads to more retired and unemployed individuals; 2) more highly education level and incomes individuals are listed, which means, samples in this study may own highly possibilities to cycle than overall situation; 3) more participants from single-family homes and from homeowner families indicate that the differences in original may cause different influences on residents' cycling behavior. Therefore, this study conduct research from following perspectives, 1) children and adults, 2) all children and children who go to school, 3) all adults, employed adults and unemployed adults, 4) origins and destinations.

3.2.3 Trip data

The dependent variable generates from two survey questions in 2010-2012 CHTS, "how many bicycles in working condition are available to people in your household?" If answers are larger than 0, the respondents will be asked, "In the past week, how many times did you ride a bicycle outside including bicycling for exercise?" Based on answers to this question, we get the data on "cycling times in one week for each person". This data presents how many times each participant rode a bicycle outside, contains cycling for entertainment and exercise in the past week. The answers to all surveys range from 1 to 50. The total number of valid cases is 51,404 (Table 3.2.3 – 1).

Table 3.2.3 – 1 Frequency Table of Cycling times in one week

Cycling times in one week								
Times	Frequency	Percent	Times	Frequency	Percent	Time	Frequency	Percent
0	36211	70.4%	11	12	/	22	2	/
1	4025	7.8%	12	96	0.2%	23	1	/
2	3590	7.0%	13	5	/	24	2	/
3	2276	4.4%	14	66	0.1%	25	23	/
4	1260	2.5%	15	44	0.1%	28	7	/
5	1421	2.8%	16	7	/	30	17	/
6	384	0.7%	17	2	/	35	4	/
7	1332	2.6%	18	3	/	40	9	/
8	110	0.2%	19	2	/	42	1	/
9	14	/	20	89	0.2%	49	1	/
10	370	0.7%	21	9	/	50	9	/
Total: N = 51,404								

"Proportions of trips that are less than 5 miles by bike" and "Mode choice as bike for trips less than 5 miles" are two alternative dependent variables to represent cycling behavior for each person. To examine the research results that generated by "cycling times in one week", especially influences from control variables on cycling, both of them calculated from 2010-2012 CHTS.

3.3 Applied Modeling

From a transportation perspective, vehicle transport is the dominant mode of travel worldwide. Empirical transportation studies about travel behaviors have naturally focused on automobile travel. However, the concepts and methods should also be useful for studies of the built environment and cycling. Handy et al. (2002) summarized that there were three types of research in travel behavior studies: simulation, aggregate and disaggregate. According to the data structure, this study could be matched as a disaggregate study. Additionally, the disaggregate study compares individual travel behavior across places with different characteristics of built environment and shows a significant advantage than aggregate study. Because aggregate study just represents cross-sectional correlations between spatial averages for travel and the built environment, but provide little evidence of a causal like between built environment and travel behaviors (Handy et al., 2002). Furthermore, this study extends an elasticity study base on the coefficients of the regression model through the disaggregate study. This elasticity study refers to estimate impacts of one percent changes in significant built environment characteristics on cycling behavior.

To test hypotheses about how different element of built environment influence cycling behaviors, a linear regression model is applied to quantify the correlations between cycling times in one week for each person and physical built environment, which is based on microeconomic demand theory (Handy et al., 2002). Because the dependent variable cycling times is considered continuous, and it is much easier to use regression models that are linearly dependent on the parameters that we wish to find as opposed to non-linear models, which add complications.

$$T = f(P, S) = \beta_0 + \mathbf{P}^{\mathrm{T}}\boldsymbol{\beta}_p + \mathbf{S}^{\mathrm{T}}\boldsymbol{\beta}_s + \varepsilon$$

Where:

T presents cycling times in one week for each person

β_0 is the constant term

$\boldsymbol{\beta}_p$ is the vector-matrix of regression coefficients of physical built environment attributes $\mathbf{P}$

$\boldsymbol{\beta}_s$ is the vector-matrix of regression coefficients of socio-demographic attributes $\mathbf{S}$

ε is a stochastic or error term

$\mathbf{P}^{\mathrm{T}}$ is the vector-matrix of physical built environment attributes

$\mathbf{S}^{\mathrm{T}}$ is the attributes vector-matrix of socio-demographic attributes

Two other models are considered for alternative dependent variables. Their results will be used to make comparisons with cycling-times model. "Mode choice as bike for trips less than 5 mile" is a categorical dependent variable as "1" and other mode choices are "0". Thus, binary logistic regression model could be conducted, where the dependent variable is a dummy variable. For proportion dependent variable – "Proportions of trips that are less than 5 miles by bike", neither linear nor logit model could be directly applied. One common method to handle this situation is to make a logit transformation this variable, and then conduct a linear regression model (Baum, 2008). The most significant limitation of this method is that it is just useful for proportions in (0, 1) interval. Using this method for this study, lots of samples that are marked with zero and one will be missing. In order to contain completed valid samples, this study used an easily method to code "0" as "0.0001", "1" as "0.9999".

CHAPTER 4

MODELING RESULTS AND ANALYSIS

4.1 Basic Model for Demographic variables

There are mainly two reasons for us to consider a basic model for socio-economic variables and cycling dependent variable. One is that control variables in basic models with unadjusted p-values of 0.15 or below are retained in initial models. As well, insignificant variables (p>0.15) are removed because there is a potential of multi-collinearity (Cervero et al., 2009). Another reason is that primary model will give out a basic squared semi-partial correlations number. By comparing the R-square for each basic model with a corresponding full model, the explained variation could show the significant influences that generated by built environment factors on cycling (Frank et al., 2005). Moreover, a combination of basic model and descriptive analysis will enlighten us about the sample characteristics, especially in the aspect of how personal attributes relate to cycling.

Table 4.1 － 1 Basic model for Cycling by demographic characteristics

	Children	Schoolchildren	Adults	Employed-adults
Gender	+	+	+	+
Age	+	+	+	+
Race	/	/	/	/
Education*			+	+
Household size	-	-	-	-
Vehicles available	-	-	-	-
Home ownership	/	/	-	-
Annual household incomes	-	-	-	/
Number of household bicycles	+	+	+	+
Household life stage**				
N	12055	11243	39400	23706
R-square	0.049	0.049	0.078	0.090
Adjusted R-square	0.048	0.047	0.077	0.089

"+": positively related to cycling; "-": negatively related to cycling; "/": insignificant.

"*": education background is not added into children-related basic models.

"**": 6 or 8 variables are involved for each type of respondents. Detail results are not shown in this Table.

Collectively, demographic variables have strong predictive powers on cycling (Table 4.1 – 1). Males tended to ride a bike more than females, which is consistent with previous studies (e.g. Heesch et al., 2012). With respect to age variables, younger adults own more cycling trips than the elderly. Among seven age groups, children between 5 years to 12 years have the largest number of cycling trips (Mean=2.29±3.29) in one week. Predictably, adults who have higher completed education level have greater possibilities to select cycling as a travel mode cycling for exercise. Unexpectedly, in all models (children, schoolchildren, adults and employed-adults) race issues show statistical insignificant for cycling behavior. Regarding the household size variables, people who live in a large family size are less likely to cycle for utilitarian or recreation. Undoubtedly, residents who from household with more bicycles and fewer vehicles, are greater likelihood to select bicycle as trip mode. Moreover, the unemployed are more likely to choose cycling as a travel mode, which is also an explanation of why this study makes distinctions between adults and employed-adults. “Home ownership” plays as a negative factor for adults and employed-adults’ cycling trips in one week. Indeed, it seems not meaningful for all children and students at the level of unadjusted probability value 0.15. When it comes to annual household incomes variables, children under 18 years old from lower household incomes settings own more cycling trips than other children from richer household incomes families. In all adults model, annual household incomes between $25,000 and $50,000 is statistical significant at 0.1 p-value level and others are not. Additionally, it shows a positive impact on cycling times. However, in employed-adults model, all annual household incomes variables are not statistical significant. A number of previous studies have pointed out that household incomes are highly-correlated to household vehicle available, and our basic models include both two sorts of variables. Thus, the insignificance of household incomes variables in adults' model and employed-adults' model should be caused by vehicle variables (e.g. Zhao, 2014). Furthermore, household life cycle also acts significant role on individual cycling behavior.

To sum, on all our models, race variables will be removed before we add built environment variables into full models. Separately, to children under 18 years old, home ownership variable is statistical insignificant and to employed-adults, annual household incomes variables should be deleted in its full model. In this stage, our results show that the R-square values in four models seem very low. However, they would be improved by adding physical built environment variables.

4.2 Full Model for Built environments and Demographic variables

4.2.1 Test for correlations

In this study, prior to estimating full models, a Pearson correlation analysis was applied to check the autocorrelation between measured built environment variables before linear regressions were conducted. Initially, a correlation coefficient less than – 0.8 or more than 0.8 is always set as high correlation (Zhao, 2014; Freedman et al., 1991).

The results of the correlation analysis show that for each random attribute, three variables represent quarter mile, half mile, and full mile radii are highly correlated with each other. For example, the variable of residential density in 1 mile radii has a 0.889 correlation coefficient when compared with the variables residential density in 0.5 mile radii and a 0.809 correlation coefficient when compared with the variable of residential density in 0.25 mile radii. However, a particular case is the attribute of activity mix. The correlation coefficient of activity mix in 1 mile and 0.25 mile radii is 0.606. Therefore, this study uses these variables in 1 mile radii to represent built environment attributes around the origin and destination, and both activity mix in 0.25 mile and 1 mile are held.

To investigate the influences of six sorts of built environment attributes (local density, diversity of land use, road connectivity, bicycle route, green space and job accessibility) on cycling, we have to keep at least one variable to represent each group. In road connectivity aspect, street intersections, road length, and bicycle-friendly road are highly correlated with each other. In a one-mile buffer around the home, street intersections have a 0.877 correlation coefficient when compared with road length and a 0.892 correlation coefficient when compared with bicycle-friendly road. In a one-mile buffer around school or workplace, street intersections have a 0.879 correlation coefficient when compared with road length and a 0.900 correlation coefficient when compared with bicycle-friendly road. The above means these three factors should not be entered into the full model to avoid autocorrelation issues. Road connectivity is defined as directness and availability of alternative routes through the network, and usually measured by 1) intersections per square mile of area, 2) straight-line distance of network distance and 3) average block length (Handy et al., 2002). We assume that in a particular buffer area, ratios of the bicycle-friendly road of total road length and average block length are approximately equal to those in other random areas. Thus, we use street intersections to perform the road connectivity. However, the limitation is that we are lack of variables to represent traffic danger road length or ratios (e.g. Winters et al., 2010).

Additionally, gravity job accessibility in 5 miles has a 0.787 correlation coefficient when compared with residential density and a 0.700 correlation coefficient when compared with employment density. Although these two values are in below 0.800, they could be used to support the highly-correlated relationships might be generated by close distance. A comparison between gravity job accessibility in 5 miles and from 5 miles to 50 miles will also show the influences of spatial zones on residents' cycling behavior (e.g. Cui et al., 2014; Winters et al., 2010).

In the sections that follow, full models are presented for predicting (1) cycling times in one week for children 5 – 18 years old; (2) cycling times in one week for schoolchildren; (3) cycling times in one week for adults; (4) cycling times in one week for employed-adults. Thus the (1) and (3) models examine how built environment attributes around home affect ordinary people's cycling times in one week. In contrast, the (2) and (4) models are extended models based on the (1) and (3) models. Students and adults' models explicitly account for characteristics of location types as "school" or "workplace" together with "home". Collectively, we believe that these quantitatively scopes will provide full insights into the influences of built environments on cycling travel in California.

4.2.2 Cycling times in one week for children under 18 years old

Table 4.2.2 – 1 Cycling times in one week for children under 18 years old

	Positive (+)	Negative (-)
Local density		Residential density (1 mile)***
Diversity of land use		
Connectivity	Street intersections (1 mile)**	
Bicycle lanes	Bike route length (1 mile)***	
Parks		Park areas (1 mile)***
N	12041	
R-square	0.053	
Adjusted R-square	0.051	

p-value 0.01: ***; p-value 0.05: **; p-value 0.1: *.

Table 4.2.2 – 1 shows that there are four sorts of built environment attributes are statistical significant at the 0.05 level. Among them, the influenced direction of residential

density is inconsistent with empirical studies. In this study, residential density in 1 mile radii is negatively associated with cycling times in one week for children under 18 years old, and the relationship is significant at the level of p<0.001. That indicates low-density communities will motivate bicycle usages for the youth in California. With respect to the variables represent diversity of land use, both "physical land use mix" and "activity mix" are failed to act as significant predictors of children's cycling behavior. For road connectivity, the chosen variable – street intersections in 1 mile is significant at the 5% probability level and shows positive effects on cycling times for children. This result is similar to the literature. However, few studies conduct separately analysis for children. Bike route length in 1 mile acts as a significant predictor and is positively related to children's cycling behavior. It means that the importance of bicycle facilities and bicycle-friendly urban design feature also cannot be ignored. Moreover, green space areas in 1 mile radii show negative influences on children's cycling times at the significance level of 1%.

4.2.3 Cycling times in one week schoolchildren

Table 4.2.3 – 1 Cycling times in one week schoolchildren

	Positive (+)		Negative (-)	
	Home	School	Home	School
Local density				Residential density (1 mile) ***
Diversity of land use				Activity mix (0.25 mile) *
Connectivity	Street intersections (1 mile) *			
Bicycle lanes		Bike route length (1 mile) ***		
Parks				
N	11219			
R-square	0.055			
Adjusted R-square	0.052			

p-value 0.01: ***; p-value 0.05: **; p-value 0.1: *.

Completed education level or employment status may be associated with cycling for transport or entertainment for adults. Regarding the children under 18 years old, whether or not to go to school could be seen as a standard of classification for cycling research. This study supposed that modeling the correlations between cycling times in one week for schoolchildren and built environment features by accounting location type as "school" would also give out new evidences to support or add findings to existing literature.

With respect to local density factors, residential density in 1 mile radii around school shows an adverse effect on cycling times at the level of $p<0.001$. Among all land use mix factors, activity mix in 0.25 miles radii around the school may also generate negative influence on cycling times for children who go to school. Above results are meaningful for policy makers to realize that to allocate the schools in low-density areas that will increase the odds of using bicycle as a transport mode for children who go to school. Considering the importance of bicycle facilities to personal safety, bike route length in 1 mile radii around the school have significantly positive impact on increasing cycling times for children.

To location type of "home", only one factor has unadjusted probability value of 0.01. Street intersections in 1 mile radii around home generate a positive influence on cycling times, which means, higher road density at the origin leads to more cycling times for local children who go to school. It indicates that the odds of using bicycle as mode to go to school will increase when the road density around home increases. It is also noteworthy that both around the home and school, green space factors have not shown significant influences on cycling times for schoolchildren.

4.2.4 Cycling times in one week for adults

Table 4.2.4 – 1 Cycling times in one week for adults

	Positive (+)	Negative (-)
Local density		Residential density (1 mile) ***
Diversity of land use	Activity mix (1 mile) **	
Connectivity	Street intersections (1 mile) ***	
Bicycle lanes	Bike route length (1 mile) ***	
Parks		
Job accessibility	Job accessibility (in 5 miles) ***	Job accessibility (from 5 to 50 miles) ***
N	39353	
R-square	0.083	
Adjusted R-square	0.083	

p-value 0.01: ***; p-value 0.05: **; p-value 0.1: *.

Here is the “largest” model (valid sample = 39353) for this study (Table 4.2.4 – 1). Gravity job accessibility factors appear to score for the adults’ model. Job accessibility has proved as an important determinant of Vehicle Miles Traveled (VMT) in the literature (Cervero & Duncan, 2006; Salon, 2014). This study examines the importance of spatial job accessibility to non-motorized behavior as cycling. Both gravity job accessibility in 5 mile radii and from 5 miles to 50 miles are statistical significant at the level of $p<0.001$. In local level, gravity job accessibility in 5 miles radii shows positive effect on cycling time for adults, which indicates that more jobs available in cycling range (less than 5 miles) will encourage employed-adults to use a bicycle as transport mode for home-to-work trip, and unemployed-adults to look for employment positions by cycling. In a regional level, gravity job accessibility from 5 mile to 50 miles is negatively related to cycling trips for adults. One reasonable explanation is that it is difficult to cycling trips to cover a distance that more than 5 miles.

Other four built environment factors are also significance. Residential density in 1 mile buffer is negatively associated with cycling times for adults at the level of $p<0.001$, which is similar to the result of children’s model but still need further research to make it robustness. Activity mix in 1 mile radii have positive influences on cycling times at the level of p<0.05. This result is well-aligned with literature, which indicates that compact and mixed-use development is likely essential to encourage non-motorized travel. Also, street intersections in 1 mile radii show positive impacts on cycling times and it is statistical significant at the level of p<0.001. Increasing the number of street intersections in a specified zone is positively related to improving cycling travels for adults in this area. Undoubtedly, bike route length in 1 mile radii will generate positive influences, and it is statistical significant at the level of p<0.001. Notably, green space variables still are statistical insignificant in this model.

4.2.5 Cycling times in one week for employed-adults

Table 4.2.5 – 1 Cycling times in one week for employed-adults

	Positive (+)		Negative (-)	
	Home	Workplace	Home	Workplace
Local density			Residential density (1 mile) ***; Employment density (1 mile) *	
Diversity of land use	Activity mix (1 mile) **			Activity mix (0.25 mile) **
Connectivity	Street intersections (1 mile) ***	Street intersections (1 mile) ***		
Bicycle lanes	Bike route length (1 mile) ***	Bike route length (1 mile) ***		
Parks				Number of parks (1 mile) **
Job accessibility	Job accessibility (5 miles) ***		Job accessibility (5 to 50 miles) ***	
N	23614			
R-square	0.099			
Adjusted R-square	0.097			

p-value 0.01: ***; p-value 0.05: **; p-value 0.1: *.

This is the "best" model for our study (Table 4.2.5 – 1). The proportions of variables achieve significance at the level of p<0.001 is much larger than the other three models. Also, in this model the amount of explained variation in cycling times in one week is greater (R-square=0.099, adjusted R-square=0.097). More importantly, based on the results of this model, we could explain the impacts of different location types as “home” and “workplace” on cycling trips of employed-adults.

In detail, all residential density, employment density, activity mix, street intersections and bike route length in 1 mile radii around the home are significance on cycling trips for employed-adults. Among them, the representatives of the diversity of land use, connectivity and bike lanes are performing as positive predictors on cycling. However, both representatives of local density are in a negative direction, and this result is still different from the literature.

Except for local density, other five built environment features around the workplace are statistical significance. Still, connectivity and bicycle lanes around the workplace act as positive predictors on cycling. Activity mix in 0.25 mile radii and number of parks in 1 mile radii are negatively associated with cycling trips for employed-adults. Unexpectedly, it is interesting to see that activity mix around the workplace is a negative powerful factor, and the number of parks in 1 mile radii around workplace achieved statistical significance. Green space has a negative impact on employed-adults’ cycling behavior, which is similar to that in schoolchildren’s model. When it comes to spatial job accessibility, their impacts on cycling of employed-adults are similar with that of adults. The representatives of both local and regional job accessibility are statistically significant at the $p<0.001$ level.

Generally speaking, the results of four full models are highly similar to empirical analyzes in North American. Several questions need to be addressed. Firstly, residential density seems negatively associate with cycling trips for all types of bicycle owners in California, which is inconsistent with almost all empirical studies. Secondly, in literature, green space acts as a positive or insignificant predictor of cycling behavior, but this study shows that the influences of green space on cycling are in a negative direction for schoolchildren and employed-adults. Last but the most important issue is that in four models, the values of R-square are below 10%. In the literature, we could commonly see the low R-square situations for cycling research, however, we should take some measure to make our results more reliable. Therefore, to test the above three questions, we use another dataset to represent person- and household-level control variables. Therefore, to test the above three questions, we will use another dataset to represent person- and household-level control variables. This dataset is generated based on 2009 Nation Household Travel Survey data (2009 NHTS) by the same methods as we applied on 2010-2012 CHTS. The limitation of this dataset is that “cycling times in one week” are not collected from interviewees who own at least one household bicycle.

4.3 Elasticity analysis

Usually, it is not easy to judge the relative importance of particular explanatory variables from linear regression model results (e.g. Zhao, 2014; Cervero, 2002). However, the coefficients in linear regressions are meaningful for elasticities. That is the percent change in the dependent variable caused by one percent change independent variables. This study applies average elasticity estimation for the explanatory variables of the built environment to address this issue (Table 4.3 – 1). The following formulation shows as a primary method for elasticities’ calculation. “Average elasticity” is measured as the average elasticities for all individuals.

$$E_{X_{kn}}^{Y_n} = \frac{\partial Y_n}{\partial X_{kn}} \times \frac{X_{kn}}{Y_n}$$

where, $E_{X_{kn}}^{Y_n}$ is cycling times elasticities of the estimated times (Y_n) of person n choosing travel mode as cycling with respect to a change in the value of *kth* variable X_{kn}.

Table 4.3 – 1 Average elasticity estimation from cycling models

Built environment features	Children		Adults	
	All children	Schoolchildren	All adults	Employed-adults
Home				
residential density (1 mile)	-0.142025		-0.171488	-0.209405
employment density (1 mile)				-0.026093
activity mix (1 mile)			0.082175	0.186702
street intersections (1 mile)	0.123786	0.130079	0.295200	0.378731
bike route length (1 mile)	0.052544		0.157021	0.145281
park areas (1 mile)	-0.037304			
Job accessibility (5 to 50 miles)			-0.144934	-0.114596
Job accessibility (5 miles)			0.109547	0.151890
School/Workplace				
residential density (1 mile)		-0.192445		
activity mix (0.25 mile)		-0.073737		-0.172040
street intersections (1 mile)				0.164248
bike route length (1 mile)		0.072866		0.186578
number of parks (1 mile)				-0.073994

Cycling times for children in one week is found to be the most sensitive to changes in residential density in 1 mile radii around the home. A 1 percent increase in this index is related to a 0.142 percent decrease in children's cycling trips. Street intersections in 1 mile buffer have an elasticity of 0.1238, which is the second-most-powerful factor influencing children's cycling behavior of all the built environment variables. Moreover, as a 1 percent increase in the length of bike route in 1 mile radii around the home, reveals a 0.05 percent growth in cycling times in one week for children. Park areas in 1 mile buffer around home show an elasticity of -0.037, which is the least important variable among four significant built environment factors.

When it comes to the model for schoolchildren, built environment variables around the school are more important than those around the home. Residential density in 1 mile radii around school plays as the most powerful predictor on cycling trips for schoolchildren. A 1 percent increase in this index is related to a 0.19 percent decrease in children's cycling trips. With respect to the diversity of land use, activity mix in 0.25 mile around the school has an elasticity of -0.074. It seems as the third-most-important variable to cycling dependent variable. Bike route length in 1 mile radii around the school has an elasticity of 0.0729. Street intersections in 1 mile radii around the home are the second-most-powerful argument, which is the same as the model for all children. As a 1 percent increase in street intersections presents a 0.13 percent growth in cycling times for children.

Again, street intersections in 1 mile radii have an elasticity of 0.2952, which shows the strongest predictive function for increasing cycling times for adults. Residential density is the second most-important variable, as a 1 percent increase in this index, reveals a 0.17 percent reduction in adults' cycling times in one week. Bike route length has an elasticity of 0.1570, which is the third powerful argument in this model. Job accessibility in 5 to 50 miles is the fourth most- important variable, as a 1 percent increase reveals a -0.14 percent reduction in adults' cycling times in one week. However, job accessibility in 5 miles shows a slight positive influence, which has an elasticity of 0.1095. The elasticity of activity mix (0.082) shows its limit impacts on cycling behavior for adults.

Significantly, street intersections in 1 mile radii around the home are still found to be the most sensitive factor on cycling trips for employed-adults. The elasticity of street intersections equals to 0.3787. Residential density in 1 mile radii around the home is the second-most powerful factors, as 1 percent increases reveals a 0.21 percent decrease in the dependent variable. More important, bike route length shows its stronger predictive power on cycling trips for employed-adults. In 1 mile radii around the workplace, bike route length has an elasticity of 0.1866, when it comes to the location type of home, its elasticity equals to 0.1452. With respect to the diversity of land use, the influences are in different directions for home and workplace. Activity mix in 1 mile around the home has an elasticity of 0.1867, which is the fourth-most sensitive factor in this model. However, activity mix in 0.25 mile around the workplace is -0.1720. For this study, another meaningful variable in this model is the number of parks in 1 mile buffer around the workplace, which shows a slight negative influence on employed-adults' cycling trips with an elasticity of -0.074.

In summary, the number of street intersections is the most powerful predictors to improve local cycling-level. One reason might be that the number of local crossings is more directly related to road connections, which have significant effects on distance and the time costs of cycling for transport (Zhao, 2014). Another reason is that traffic safety issues related to vehicles was the most important factor prevent residents from bicycling. Bicycle-related traffic accidents occurred more frequently between cars and bicycles at main-road and expressway. Street intersections would lessen the impact of automobile traffic at main-road and expressway by slowing it down. Moreover, traffic pollution is another issue related to cycling and traffic calming around the intersections might eliminate noise and pollution. Residential density also shows strong negative impacts on cycling behavior, especially for children and schoolchildren. However, the impacts of green space on cycling for schoolchildren and employed-adults are not precise as that of residential density.

Furthermore, compared with bike route length, the number of street intersections and residential density are not easily to be improved in most urban areas. Therefore, from a utilitarian view, to encourage more residents to cycling for transport or recreation, increasing the length of bike lane is a more directly method than changing other features in urban structure design.

4.4 A summary comparison of 2010-2012 CHTS and 2009 NHTS full models

As mentioned in *3.2.2 Demographic variables and characteristics*, to make these results robust, this study estimated relationships between built environments and cycling activity using a second dataset – 2009 NHTS. The California portion of the 2009 National Household Travel Survey is extremely similar to 2010 – 2012 California Household Travel Survey. In both travel surveys, each person in surveyed households provided the full details of their cycling activities for an assigned week. In particular, the entire NHTS California sample includes information from nearly 45,000 respondents. Similarity, the result here focus on those individuals provided sufficient information for analysis. However, the difference between 2012 – 2012 CHTS and 2009 NHTS is that individuals in 2009 NHTS are not asked the question: "how many bicycles in your household?" Therefore, our final sample of 2009 NHTS California includes nearly 38,000 individuals, which contains a number of non-bicycle owners.

Unexpectedly, 2010-2012 CHTS regression models showed that residential density always generates significant negative influences on cycling. This direction is not consistent with previous studies. When it comes to green space factor, how does it affect cycling? It is still in question because from above only two variables are statistically significant for cycling dependent variables, and there are totally twelve green space related arguments in four full models. Table 4.4 – 1 presents the results of residential density and green space variables in 2009 NHTS models.

Table 4.4 – 1 Residential density and Green Space by 2009 NHTS

	Residential density		Green Space			
	Home	Workplace	Home		Workplace	
			Number	Area	Number	Area
Children	Insignificant	/	-	/	/	/
Adults	-	/	Insignificant	+	/	/
Employed-adults	-	Insignificant	Insignificant	+	Insignificant	Insignificant

"+": positive; "-": negative; "/": not contained in model.

When taken socio-demographic variables from 2009 NHTS, residential density in 1 mile radii around the home are statistically significant, and negatively associated with adults' and employed-adults' cycling behavior. This result is well-aligned with 2010-2012 CHTS based models but is still in reverse literature-direction. Still, influences from green space are not always significant in 2009 NHTS based model. Among three meaningful green space variables, park area in 1 mile radii around the home is positively related to adults' and employed-adults' cycling trips. However, the number of parks in 1 mile radii around the home is a negative predictor to cycling for children. Therefore, influences from green space on cycling are still difficult to be defined. Furthermore, to check the abnormal performance of residential density, we conduct further research to investigate the correlations between residential density and average cycling times by 2010 – 2012 CHTS. Eleven different residential density zones are considered by statistical summary (Table 4.4 – 2). Also, the mean value of cycling times for these cyclists in a specified area are calculated.

Table 4.4 – 2 Residential density classification and average cycling times

		Children		Schoolchildren		Adults		Employed-adult	
Location types		Home: 1 mile		School: 1 mile		Home: 1 mile		Home: 1 mile	
Density Range	Code	Mean	N	Mean	N	Mean	N	Mean	N
0	0	2.33	27	4.26	19	0.74	66	0.77	35
(0 , 0.0005]	1	1.92	1072	1.98	868	0.57	4043	0.57	2121
(0.0005 , 0.0010]	2	1.99	1511	1.94	1259	0.59	4521	0.58	2666
(0.0010 , 0.0015]	3	1.85	1859	2.08	1845	0.68	5804	0.70	3568
(0.0015 , 0.0020]	4	2.07	1945	2.04	2003	0.79	6237	0.81	3813
(0.0020 , 0.0025]	5	2.00	1618	2.07	1502	0.76	5153	0.77	3127
(0.0025 , 0.0030]	6	1.94	1115	1.89	1113	0.83	3605	0.88	2203
(0.0030 , 0.0035]	7	2.00	802	1.83	731	0.76	2867	0.83	1798
(0.0035 , 0.0040]	8	1.85	607	1.80	537	0.85	1934	0.87	1192
(0.0040 , 0.0045]	9	1.85	434	1.80	388	1.05	1396	1.18	847
(0.0045 , +∞]	10	1.88	1052	1.66	955	1.22	3728	1.32	2245
			12042		11220		39354		23615

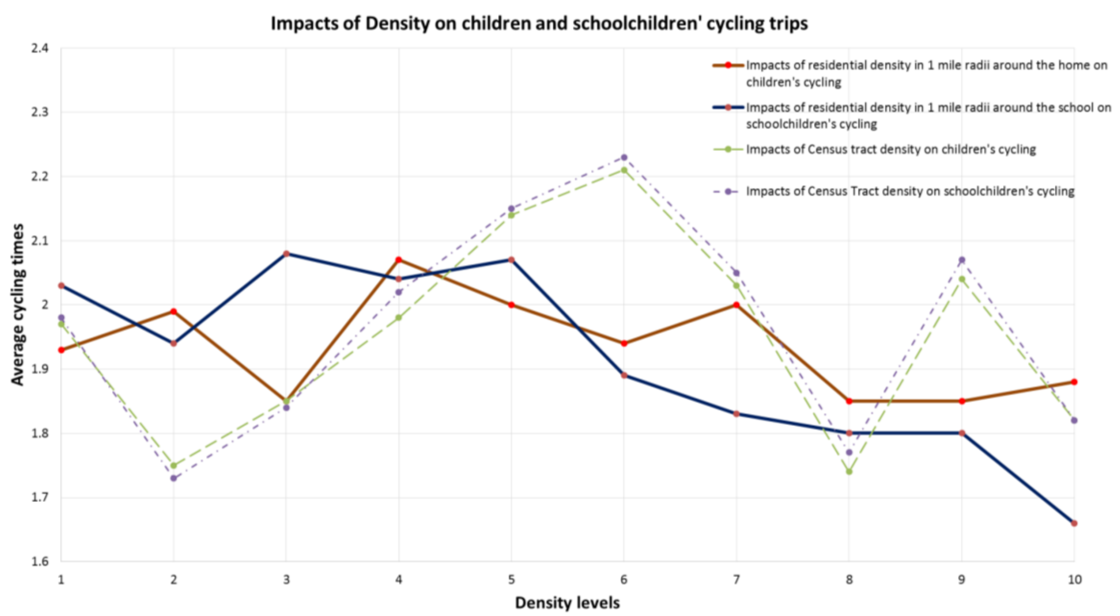

Figure 4.4 – 1 Impacts of residential density on cycling times for children and schoolchildren

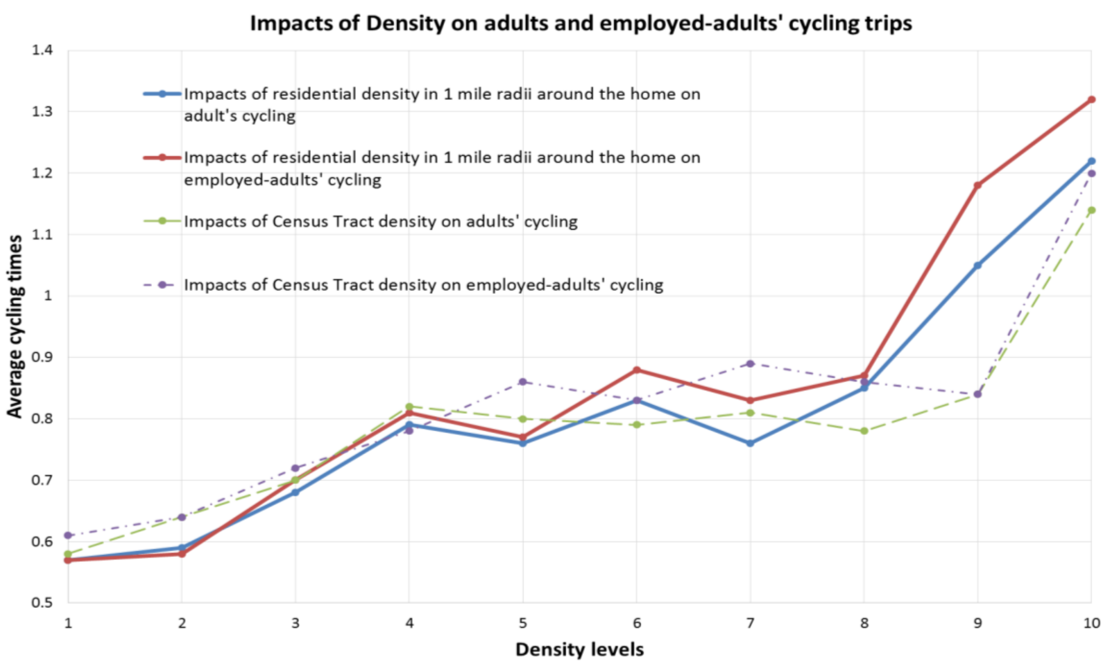

Figure 4.4 – 2 Impacts of residential density on cycling times for adults and employed-adults

Figure 4.4 – 1 illustrates the impact of residential density on average cycling times for children and schoolchildren. Through the general tendency of two lines, we could clearly see the different influences of density on children and schoolchildren. Firstly, residential density is negatively related students' cycling behavior, which is consistent with the results of 2010-2012 CHTS regression models and Larsen's study (2009). This phenomenon could be explained as increasing residential densities are associated with increased levels of automobile traffic and crime, which increases danger (real and perceived) and might be a deterrent to cycling for children (e.g. Larsen et al., 2009). Secondly, residential density seems like a "fluctuant" factor to cycling trips of the whole children group. Figure 4.4 – 2 depicts that residential density is positively related to both adults' and employed-adults' cycling trips. That result is a little distinguished from 2010-2012 CHTS regression models, because both Figures ignore the issue of samples' distribution. Further research could consider how residential density works on individuals'

cycling in each classified zone. Collectively, residential density always has a significant effect on cycling trips. However, its influential direction on cycling trips of different people still need further research to confirm.

Another flaw of 2010-2012 CHTS regression models might weaken this study is that the data is not well-fitted each regression line. The R-square values of all models are extremely low. Unfortunately, after using 2009 NHTS California data, R-square results do not perform better, and even worse than 2010 – 2012 CHTS models (Table 4.4 – 3).

Table 4.4 – 3 R-square comparison I (2012-2012 CHTS VS. 2009 NHTS)

	R-square (Adjusted R-square)		Valid samples	
	2010-2012 CHTS	2009 NHTS	2010-2012 CHTS	2009 NHTS
Children	0.053 (0.051)	0.040 (0.036)	12041	6143
Adults	0.083 (0.083)	0.024 (0.023)	39353	31492
Employed-adults	0.099 (0.097)	0.035 (0.032)	23614	16463

Table 4.4 – 4 R-Square comparison II (Basic models VS. Full models by 2010-2012 CHTS)

	R-square (Adjusted R-square)	
	Basic model	Full model
Children	0.049 (0.048)	0.053 (0.051)
Schoolchildren	0.049 (0.047)	0.055 (0.052)
Adults	0.078 (0.078)	0.083 (0.083)
Employed-adults	0.090 (0.089)	0.099 (0.097)

In literature, disaggregate active transport study often result in low R-squares. For instance, Greenwald & Boarnet (2001) used number of non-work walking trips per person over two-day travel diary period as dependent variable generate four R-squares that between 5%-10% level. Moreover, in another disaggregate cycling study, Frank et al. (2005) created a "walkability index" (sum of weighted scores of land use variables. The R-squares of Frank's two linear regression models are both between 5%-10%. The significance of "walkability index" to was addressed by the improvement of R-square in the full model, which equals to 0.02. Cycling behavior is relatively unpredictable at individuals-level, which is similar to walking and other cross-sectional studies. While, for an individual cycling activity, bicycle ownership could seem as powerful predictive factor for people's cycling trips. That may explain why R-squares of 2010-2012 CHTS full model are much higher than that of 2009 NHTS full model.

In the future study, adding self-selection related factors would promote squared semi-partial correlations to a new level (e.g. Cao et al., 2006; Handy et al., 2005&2006). To this study, basic models include only the demographic variables explain less variances than full models include both the demographic and built environment variables (Table 4.4 – 4). Especially for employed adults, the total amount of variance explained increased a small but significant amount (R-square=0.099), an increase of 1% in the explained variation. The increasing of R-squares in full models show that built environment characteristics are powerful in its relationship with individual cycling behaviors.

CHAPTER 5

CONCLUSION

5.1 Overview

We can now reflect on the original questions that motivated this study: how the built environments, as local density, diversity of land use, road connectivity and bike lane, affect cycling? Additionally, whether urban green space and job accessibility will generate significant influences on cycling behaviors of individuals? Do social status and location types affect cycling? Also, if there are impacts, how to improve cycling trips during the planning process? This study corroborates previous work regarding the following aspects: 1) it shows positive impacts of diversity of land use, road connectivity, bike lane and local job accessibility in general. 2) However, impacts from regional job accessibility are in the reverse direction. 3) Road connectivity is an effectiveness factor to improve cycling trips in California. 4) With respect to local density, other issues should account for answering the question: "how does residential density affect cycling in California?" However, considering other traffic issues in practice planning, it is difficult to increase the number of street intersections. In recent years, almost all major cities in European and North America are trying to install bicycle lanes to encourage active travels.

Improving the built and transportation environments for cycling may help promote general cycling levels in California, it is by no mean insignificant for planners to realize that decisions to ride a bicycle seems to be mainly determined by personal, and not environmental, attributes. Children own more cycling trips than adults. Being a male, a renter or an unemployed will increase the odds of cycling as well. Moreover, people with higher completed education background have a preference on cycling than others. While race does not show a significant relationship with the likelihood of cycling. Among household-level attributes, larger household size, more household vehicles (a likely proxy for income) and fewer household bicycles are negatively associated with cycling behaviors. Additionally, the household life cycle will also generate a significant impact on cycling behavior of individuals.

The purpose of this study is to contribute to an academic literature on how physical built environment factors affect cycling. This study tests positive or negative impacts on cycling behaviors that are caused by different physical built environment attributes. Most of them have been put forward by previous studies. With a comprehensive understanding of how built environment works on cycling, decision makers in California local and regional could take necessary planning and policy interventions to encourage residents to ride a bike instead of using motor vehicles. Also, dwellers will be aware of the importance of living environment to daily physical activities and healthy.

5.2 Limitation and Future Research

The generalizability of this study is limited to its particular data structure, especially in the control variables' aspect. Comparing with 2010 California Census summary, socio-demographic variables from 2010 CHTS have its own characteristics: 1) more elderly and children are contained, which leads to more retired and unemployed individuals; 2) more highly education level and incomes individuals, together with more participants from single-family homes and from homeowner families. This study fails to contain all possible interaction effects, and further research is needed for weighting samples to reflect the situation of the whole California. If there is substantial difference between the response distribution and the realistic population distribution, weighting could make the survey sample represent the whole group. Most previous studies support a post-stratification weights, which are meant to adjust survey data to compensate for the fact that different types of people have different likelihoods of responding to the survey and being represented in the dataset (e.g. Salon, 2014). However, in social science research, the purpose of weighting is not to make regression model statistical meaningful. Survey weighting is not always plausible when it comes to how to use weights to estimate anything more complicated than a simple mean or ratios, and standard errors are tricky even with simple weighted means (Gelman, 2007). Another limitation may be related to spatial autocorrelation. Although all environmental measures are disaggregated and taken based on the household location of individual respondents, buffer standards captured at the 1 mile radii from home, school and workplace or neighborhood structures may have some level of spatial dependency. To solve this problem, adding a spatial autocorrelation term or using hierarchical models based on locations may be possible. However, both treatments are constrained by many assumptions, such as complete spatial randomness, which is used to maximize the generalizability of the results. Furthermore, this study fails to conclude the influences of self-selection on cycling. Self-selection data is always generated by asking individuals about their preferences and attitude directly. Residential self-selection is important in explaining active travel behavior (Cao et al., 2006; Handy et al., 2006).

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APPENDIX A

A COMPARISON OF 2010 CALIFORNIA CENSUS SUMMARY AND 2010-2012 CHTS FOR DEMOGRAPHIC CHARACTERISTICS

Variable	2010 California Census Summary ①	2010-2012 California Household Travel Survey		Sampling Error
	Percent	Mean (±S.D.)	Percent	
Valid samples (each person)	**N = 37,253,956**	**N = 51,485**		
Gender (Male / not)	49.7%		50.2%	+ 0.5%
Age				
5 to 12 years	10.9%	40.19 (±20.53)	12.7%	+ 1.8%
13 to 17 years	7.3%		9.8%	+ 2.5%
18 to 34 years	24.8%		15.4%	- 9.4%
35 to 44 years	13.9%		13.6%	- 0.3%
45 to 54 years	14.1%		19.3%	+ 5.2%
55 to 64 years	10.8%		18.7%	+ 7.9%
65 years and over	11.3%		10.5%	- 0.8%
Education				
not high school graduated or less	19.3%		27.5%	+ 8.2%
high school graduates	20.8%		14.0%	- 6.8%
with some college credit but no degree	22.2%		13.3%	- 8.9%
with associate or technical school degree	7.6%		8.1%	+ 0.5%
hold bachelor's or undergraduate degree	19.1%		20.5%	+ 1.4%
hold graduated degree	11.0%		16.6%	+ 5.6%
Employment status* (employed/not)	87.2%		51.4%	- 35.8%
Race				
Hispanic	37.6%		25.5%	- 12.1%
White not Hispanic	40.1%		62.0%	+ 21.9%
Some other races (include two or more races)	22.3%		12.5%	- 9.8%
Valid sample (unit of household)	**N = 13,682,976**	**N = 19,175**		
Household size ②				
1-person household	23.3%	2.96 (±1.43)	13.0%	- 10.3%
2-person household	29.1%		33.5%	+ 4.4%
3-person household	16.2%		19.0%	+ 2.8%
4-or-more-person household	31.4%		34.6%	+ 3.2%
Home owner	55.6%		80.9%	+ 25.3%
Units in Structure				
Single family house not attach	57.8%		79.6%	+ 21.8%
Single family house attached	7.2%		7.0%	- 0.2%
A mobile home	3.8%		1.9%	- 1.9%
Building with 2 to 4 layers	8.2%		3.2%	- 5.0%
Building with 5 to 19 layers	11.3%		4.5%	- 6.8%
Building with more than 20 layers	11.6%		3.8%	- 7.8%
Boat van	0.1%		0%*	- 0.1%
Vehicles Available				
No vehicles available	7.8%	2.06 (±0.99)	3.5%	- 4.3%
1 vehicle available	32.2%		22.2%	- 10.0%
2 vehicles available	37.4%		48.7%	+ 11.3%
3 or more vehicles available	22.6%		25.6%	+ 3.0%
Number of household bicycles				
one household bicycle		2.43 (±1.57)	31.6%	
two household bicycles			32.7%	
Three or more household bicycles			35.7%	
Household incomes				
annual incomes less than $25,000	21.6%		11.0%	- 10.6%
annual incomes $25,000 -$50,000	22.3%		16.0%	- 6.3%
annual incomes $50,000 - $100,000	29.8%		33.2%	+ 3.4%
annual incomes more than $100,000	26.3%		39.8%	+ 13.5%
Household life stage ③				
one adult, 18-64, no children	21.5%		9.9%	- 11.6%

2+ adults, at least one adult 18-64, no children	35.8%		41.1%	+ 5.3%
one adult, youngest child 0-5	0.9%		0.5%	- 0.4%
2+ adults, youngest child 0-5	9.5%		11.7%	+ 2.2%
one adult, youngest child 6-17	2.6%		2.3%	- 0.3%
2+ adults, youngest child 6-17	12.1%		25.7%	+ 13.6%
one adult, over 64, no children	9.7%		3.0%	- 6.7%
2+ adults, all adults over 64, no children	7.8%		5.7%	- 2.1%

① : 1) 2010 Census Congressional District Summary File (113th Congress); 2) 2010 American Community Survey 1-Year Estimates; 3) 2010 Census Summary File 1;

② : Personal attributes related household size are calculated based on 2010 California Census that average household size equals to 2.9.

③ :

Life Stage Code	Census Definition	Travel Survey Definition
1	one adult, 18-64, no children	one adult, 18-64, no children
2	2+ adults, householder 18-64, no children	2+ adults, at least one adult 18-64, no children
3	one adult, youngest related child 0-5	one adult, youngest child 0-5
4	2+ adults, youngest related child 0-5	2+ adults, youngest child 0-5
5	one adult, youngest related child 6-17	one adult, youngest child 6-17
6	2+ adults, youngest related child 6-17	2+ adults, youngest child 6-17
7	one adult, over 64, no children	one adult, over 64, no children
8	2+ adults, householder over 64, no children	2+ adults, all adults over 64, no children

Source: Salon, Final Report Quantifying the effect of local government actions on VMT 2014

APPENDIX B

DEMOGRAPHIC CHARACTERISTICS AND CYCLING TIMES IN 2010-2012 CHTS

Variable	Cycling times in one week (N = 51,404)		Proportions of trips that are less than 5 miles by bike in one day (N = 22,635)		Mode choice as bicycle for trips less than 5 miles in one day (N = 78,869, bike for trips= 2, 166)	
	Mean (±S.D.)	Percent	Mean (%) (±S.D.)	Percent	Mean (%) (±S.D.)	Percent
Gender (Male / not)	1.36 (±2.93) / 0.74 (±1.99)	50.3%	1.88% (±9.89%) /1.03% (±7.00%)	49.9%	3.79% (±0.19) /1.79% (±0.13)	47.8%
Age						
5 to 12 years	2.29 (±3.29)	13.9%	1.77% (±9.50%)	14.9%	2.84% (±0.17)	14.0%
13 to 17 years	1.45 (±3.16)	9.6%	1.94% (±9.80%)	10.3%	3.83% (±0.19)	9.5%
18 to 34 years	0.95 (±2.59)	14.9%	1.10% (±7.43%)	14.0%	2.46% (±0.16)	13.1%
35 to 44 years	0.82 (±2.20)	13.5%	1.50% (±8.72%)	13.5%	2.66% (±0.16)	15.6%
45 to 54 years	0.80 (±2.13)	19.1%	1.38% (±8.40%)	19.8%	2.68% (±0.16)	21.7%
55 to 64 years	0.71 (±1.94)	18.6%	1.45% (±8.69%)	18.3%	2.78% (±0.16)	17.9%
65 years and over	0.56 (±1.95)	10.4%	1.01% (±6.89%)	9.0%	2.02% (±0.14)	8.1%
Education						
not high school graduated or less	1.74 (±3.14)	28.4%	1.69% (±9.21%)	30.1%	2.98% (±0.17)	28.3%
high school graduates	0.77 (±2.36)	13.7%	0.97% (±7.13%)	12.7%	2.04% (±0.14)	11.5%
with some college credit but no degree	0.71 (±2.31)	13.0%	0.95% (±7.04%)	12.5%	2.01% (±0.14)	12.2%
with associate or technical school degree	0.62 (±1.76)	8.0%	1.00% (±7.02%)	7.4%	2.13% (±0.14)	7.3%
hold bachelor’s or undergraduate degree	0.75 (±1.99)	20.4%	1.35% (±8.09%)	20.3%	2.46% (±0.16)	22.0%
hold graduated degree	0.95 (±2.29)	16.5%	2.12%(±10.41%)	16.8%	3.89% (±0.19)	18.6%
Employment status (employed/not)	0.81 (±2.21) / 1.30 (±2.80)	50.8%	1.46% (±8.58%) / 1.45% (±8.58%	50.6%	2.81% (±0.17)/ 2.68% (±0.16)	52.0%
Race						
Hispanic	1.19 (±2.62)	25.6%	1.04% (±7.18%)	26.8%	1.85% (±0.14)	26.0%
White not Hispanic	1.00 (±2.46)	62.0%	1.68% (±9.21%)	61.0%	3.16% (±0.18)	62.2%
Some other races (include two or more races)	1.00 (±2.65)	12.4%	1.24% (±8.08%)	12.2%	2.55% (±0.16)	11.9%
Household size						
1-person household	1.36 (±3.12)	4.6%	2.30%(±11.05%)	3.8%	4.36% (±0.20)	4.4%
2-person household	0.81 (±2.17)	23.7%	1.48% (±8.68%)	21.5%	3.03% (±0.17)	21.0%
3-person household	0.90 (±2.42)	19.4%	1.44% (±8.63%)	19.7%	3.08% (±0.17)	18.7%
4-or-more-person household	1.19 (±2.64)	52.4%	1.39% (±8.32%)	54.9%	2.40% (±0.15)	56.0%
Home owner	0.96 (±2.32) / 1.47 (±3.24)	81.2%	1.38% (±8.35%)/ 1.77% (±9.54%)	81.8%	2.59% (±0.16) / 3.39 (±0.18)	80.2%
Units in Structure						
Single family house not attach	0.99 (±2.37)	82.6%	1.36% (±8.25%)	83.7%	2.56% (±0.16)	81.5%
Single family house attached	1.24 (±2.84)	6.5%	1.77% (±9.20%)	6.7%	3.08% (±0.17)	7.3%
A mobile home	1.34 (±2.55)	1.7%	2.13%(±10.71%)	1.2%	3.80% (±0.19)	1.2%
Building with 2 to 4 layers	1.65 (±3.63)	2.8%	2.34%(±11.02%)	2.8%	4.53% (±0.21)	3.4%
Building with 5 to 19 layers	1.49 (±3.80)	3.4%	1.50% (±9.32%)	3.3%	3.22% (±0.18)	3.9%
Building with more than 20 layers	1.20 (±2.80)	3.0%	2.62%(±11.77%)	2.3%	4.08% (±0.20)	2.8%
Vehicle available						
No vehicles available	2.62 (±4.63)	2.5%	3.60%(±13.99%)	2.9%	5.45% (±0.23)	4.2%
1 vehicle available	1.42 (±3.27)	16.5%	2.42%(±11.29%)	15.6%	4.92% (±0.22)	16.9%
2 vehicles available	1.01 (±2.32)	49.7%	1.45% (±8.55%)	49.6%	2.47% (±0.16)	49.9%
3 or more vehicles available	0.80 (±2.04)	31.3%	0.80% (±6.01%)	32.0%	1.58% (±0.13)	29.0%
Number of household bicycles						
one household bicycle	0.64 (±2.02)	24.9%	1.07% (±7.45%)	23.8%	1.94% (±0.14)	23.0%
two household bicycles	0.81 (±2.24)	30.6%	1.00% (±6.81%)	30.3%	1.95% (±0.14)	29.4%
Three or more household bicycles	1.45 (±2.89)	44.5%	1.96%(±10.03%)	45.8%	3.63% (±0.19)	47.6%
Household incomes						
annual incomes less than $25,000	1.50 (±3.29)	10.7%	1.43% (±8.58%)	10.6%	2.41% (±0.15)	11.3%
annual incomes $25,000 -$50,000	1.11 (±2.65)	15.7%	1.28% (±8.00%)	15.9%	2.53% (±0.16)	15.1%
annual incomes $50,000 - $100,000	0.96 (±2.34)	32.2%	1.24% (±8.04%)	30.7%	2.66% (±0.16)	29.7%
annual incomes more than $100,000	0.99 (±2.38)	41.3%	1.68% (±9.14%)	42.8%	2.97% (±0.17)	43.9%
Household life stage						
one adult, 18-64, no children	1.43 (±3.06)	3.7%	2.42%(±11.26%)	3.2%	4.26% (±0.20)	3.7%
2+ adults, at least one adult 18-64, no children	0.77 (±2.13)	36.1%	1.39% (±8.41%)	34.5%	2.90% (±0.17)	32.0%
one adult, youngest child 0-5	2.37 (±4.57)	0.4%	0.41% (±4.04%)	0.4%	0.55% (±0.07)	0.5%
2+ adults, youngest child 0-5	1.37 (±2.82)	15.1%	1.20% (±7.79%)	15.6%	2.45% (±0.16)	16.1%
one adult, youngest child 6-17	1.44 (±3.24)	2.2%	1.27% (±7.46%)	2.3%	2.96% (±0.17)	2.5%
2+ adults, youngest child 6-17	1.16 (±2.61)	38.4%	1.61% (±8.99%)	40.7%	2.68% (±0.16)	42.2%
one adult, over 64, no children	1.12 (±3.32)	1.0%	1.71% (±9.94%)	0.6%	4.90% (±0.22)	0.6%
2+ adults, all adults over 64, no children	0.58 (±1.75)	3.2%	0.52% (±5.19%)	2.6%	1.04% (±0.10)	2.3%

APPENDIX C

BASIC MODEL RESULTS

Cycling times in one week for children under 18 years old (Demographic Variables)

Variable	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
constant	2.164	.000	.147	14.715	1.876	2.452
Gender						
Male	.737	.000	.058	12.682	.623	.851
Age						
5 to 12 years	-	-	-	-	-	-
13 to 17 years	-.358	.000	.031	-11.387	-.419	-.296
Race						
Hispanic	-.129	.202	.101	-1.276	-.328	.069
White but not Hispanic	-.111	.238	.095	-1.179	-.297	.074
Household size						
2-person household	.260	.042	.128	2.038	.010	.511
3-person household	.037	.228	.031	1.206	-.023	.098
4-or-more-person household	-	-	-	-	-	-
Vehicles available						
No vehicles available	.231	.289	.218	1.060	-.196	.657
1 vehicle available	.127	.023	.056	2.267	.017	.236
2 vehicles available	-.006	.805	.024	-.247	-.052	.040
3 or more vehicles available	-	-	-	-	-	-
Home ownership						
Home owner	-.052	.529	.082	-.629	-.213	.110
Annual household incomes						
incomes less than $25,000	.824	.000	.119	6.918	.591	1.058
incomes $25,000 -$50,000	.251	.000	.048	5.226	.157	.346
incomes $50,000 -$100,000	.060	.012	.024	2.519	.013	.107
incomes more than $100,000	-	-	-	-	-	-
Number of household bicycle						
One household bicycle	-1.000	.000	.092	-10.812	-1.181	-.818
Two household bicycles	-.322	.000	.037	-8.727	-.394	-.249
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, youngest child 0-5	.204	.048	.103	1.980	.002	.405
2+ adults, youngest child 0-5	-	-	-	-	-	-
one adult, youngest child 6-17	-.126	.001	.037	-3.426	-.198	-.054
2+ adults, youngest child 6-17	-.038	.002	.012	-3.116	-.063	-.014
N	12055					
R-square	0.049					
Adjusted R-square	0.048					

Cycling times in one week for schoolchildren (Demographic Variables)

Variables	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
Constant	2.165	.000	.155	14.004	1.862	2.468
Gender						
Male	.758	.000	.061	12.419	.639	.878
Age						
5 to 12 years	-	-	-	-	-	-
13 to 17 years	-.347	.000	.033	-10.523	-.412	-.282
Race						
Hispanic	-.128	.230	.107	-1.199	-.337	.081
White but not Hispanic	-.117	.237	.099	-1.184	-.311	.077

Household size						
2-person household	.246	.064	.133	1.853	-.014	.506
3-person household	.041	.207	.032	1.263	-.022	.104
4-or-more-person household	-	-	-	-	-	-
Vehicles available						
No vehicles available	.327	.151	.228	1.436	-.119	.773
1 vehicle available	.156	.008	.059	2.642	.040	.271
2 vehicles available	.001	.956	.025	.055	-.047	.050
3 or more vehicles available	-	-	-	-	-	-
Home ownership						
Home owner	-.072	.408	.087	-.827	-.241	.098
Annual household incomes						
incomes less than $25,000	.836	.000	.127	6.608	.588	1.084
incomes $25,000 -$50,000	.249	.000	.051	4.880	.149	.349
incomes $50,000 -$100,000	.067	.008	.025	2.658	.018	.117
incomes more than $100,000	-	-	-	-	-	-
Number of household bicycle						
One household bicycle	-.993	.000	.097	-10.243	-1.183	-.803
Two household bicycles	-.326	.000	.039	-8.420	-.402	-.250
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, youngest child 0-5	.159	.143	.108	1.466	-.054	.371
2+ adults, youngest child 0-5	-	-	-	-	-	-
one adult, youngest child 6-17	-.134	.000	.038	-3.489	-.209	-.059
2+ adults, youngest child 6-17	-.042	.001	.013	-3.206	-.067	-.016
N	11243					
R-square	0.049					
Adjusted R-square	0.047					

Cycling times in one week for adults (Demographic Variables)

Variables	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
Constant	.862	.000	.064	13.489	.737	.987
Gender						
Male	.557	.000	.021	26.232	.515	.599
Age						
18 to 34 years	.388	.000	.036	10.846	.318	.459
35 to 44 years	.075	.000	.019	3.987	.038	.112
45 to 54 years	.048	.000	.011	4.520	.027	.069
55 to 64 years	-	-	-	-	-	-
65 years and over	-.026	.003	.009	-2.999	-.043	-.009
Education						
not high school graduated or less	-.309	.000	.055	-5.670	-.416	-.202
high school graduates	-.107	.000	.019	-5.711	-.144	-.071
with some college credit but no degree	-.081	.000	.012	-6.650	-.104	-.057
with associate or technical school degree	-.073	.000	.010	-7.169	-.093	-.053
hold bachelor’s or undergraduate degree	-.037	.000	.006	-6.044	-.050	-.025
hold graduated degree	-	-	-	-	-	-
Race						
Hispanic	-.042	.283	.039	-1.073	-.119	.035
White but not Hispanic	.028	.393	.033	.854	-.036	.093
Household size						
1-person household	-	-	-	-	-	-
2-person household	.098	.000	.020	4.843	.058	.138
3-person household	.033	.002	.011	3.089	.012	.054
4-or-more-person household	-	-	-	-	-	-

Vehicle available						
No vehicles available	2.181	.000	.077	28.495	2.031	2.331
1 vehicle available	.348	.000	.019	17.937	.310	.386
2 vehicles available	.047	.000	.009	5.331	.030	.064
3 or more vehicles available	-	-	-	-	-	-
Home ownership						
Home owner	-.168	.000	.032	-5.215	-.232	-.105
Annual household incomes						
incomes less than $25,000	.051	.280	.047	1.080	-.041	.143
incomes $25,000 -$50,000	.032	.075	.018	1.783	-.003	.067
incomes $50,000 -$100,000	.011	.196	.009	1.294	-.006	.028
incomes more than $100,000	-	-	-	-	-	-
Number of household bicycle						
One household bicycle	-.877	.000	.029	-29.995	-.934	-.819
Two household bicycles	-.297	.000	.013	-22.351	-.323	-.271
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, 18-64, no children	.344	.000	.065	5.283	.216	.471
2+ adults, at least one adult 18-64, no children	-	-	-	-	-	-
one adult, youngest child 0-5	-.103	.167	.074	-1.381	-.249	.043
2+ adults, youngest child 0-5	-.054	.000	.011	-4.958	-.075	-.033
one adult, youngest child 6-17	-.113	.000	.021	-5.399	-.154	-.072
2+ adults, youngest child 6-17	-.035	.000	.006	-6.013	-.046	-.024
one adult, over 64, no children	.058	.000	.016	3.694	.027	.088
2+ adults, all adults over 64, no children	.006	.494	.008	.683	-.010	.022
N	39400					
R-square	0.078					
Adjusted R-square	0.077					

Cycling times in one week for employed-adults (Demographic Variables)

Variables	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
Constant	1.243	.000	.082	15.221	1.083	1.403
Gender						
Male	.516	.000	.028	18.446	.461	.571
Age						
18 to 34 years	-	-	-	-	-	-
35 to 44 years	-.121	.000	.023	-5.391	-.166	-.077
45 to 54 years	-.099	.000	.014	-7.157	-.126	-.072
55 to 64 years	-.099	.000	.011	-8.781	-.121	-.077
65 years and over	-.086	.000	.018	-4.757	-.122	-.051
Education						
not high school graduated or less	-.354	.000	.076	-4.642	-.504	-.205
high school graduates	-.144	.000	.025	-5.751	-.193	-.095
with some college credit but no degree	-.080	.000	.016	-5.092	-.110	-.049
with associate or technical school degree	-.069	.000	.013	-5.222	-.095	-.043
hold bachelor's or undergraduate degree	-.038	.000	.008	-4.851	-.053	-.023
hold graduated degree	-	-	-	-	-	-
Race						
Hispanic	-.015	.773	.050	-.289	-.113	.084
White but not Hispanic	.056	.185	.042	1.325	-.027	.139
Household size						
1-person household	-	-	-	-	-	-
2-person household	.095	.000	.027	3.587	.043	.147

3-person household	.036	.008	.013	2.647	.009	.062
4-or-more-person household	-	-	-	-	-	-
Vehicle available						
No vehicles available	3.202	.000	.112	28.648	2.982	3.421
1 vehicle available	.472	.000	.027	17.553	.419	.525
2 vehicles available	.049	.000	.011	4.262	.026	.071
3 or more vehicles available	-	-	-	-	-	-
Home ownership						
Home owner	-.136	.001	.042	-3.245	-.219	-.054
Annual household incomes						
incomes less than $25,000	-.083	.210	.066	-1.253	-.213	.047
incomes $25,000 -$50,000	.003	.890	.024	.138	-.044	.050
incomes $50,000 -$100,000	-	-	-	-	-	-
incomes more than $100,000	-.009	.286	.008	-1.067	-.025	.007
Number of household bicycle						
One household bicycle	-.902	.000	.038	-23.455	-.977	-.826
Two household bicycles	-.312	.000	.017	-18.174	-.345	-.278
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, 18-64, no children	.144	.087	.084	1.713	-.021	.308
2+ adults, at least one adult 18-64, no children	-	-	-	-	-	-
one adult, youngest child 0-5	-.124	.189	.094	-1.313	-.308	.061
2+ adults, youngest child 0-5	-.048	.001	.014	-3.475	-.075	-.021
one adult, youngest child 6-17	-.169	.000	.026	-6.621	-.219	-.119
2+ adults, youngest child 6-17	-.028	.000	.007	-3.722	-.042	-.013
one adult, over 64, no children	.022	.442	.029	.768	-.035	.080
2+ adults, all adults over 64, no children	-.027	.131	.018	-1.512	-.062	.008
N	23706					
R-square	0.090					
Adjusted R-square	0.089					

APPENDIX D

FULL MODEL RESULTS

Cycling times in one week for children under 18 years old

Variable	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
constant	2.189	.000	.184	11.876	1.827	2.550
Built environment features						
Single-family homes	-	-	-	-	-	-
Multiple-family homes	-.068	.228	.057	-1.206	-.180	.043
h_ residential density (1 mile) *	-111.841	.000	29.425	-3.801	-169.519	-54.162
h_ employment density (1 mile)	-28.366	.297	27.187	-1.043	-81.658	24.926
h_ phy land use density (1 mile)	-.160	.286	.150	-1.068	-.453	.134
h_ activity mix (0.25 mile)	.029	.897	.223	.129	-.408	.466
h_ activity mix (1 mile)	.133	.615	.264	.503	-.385	.651
**h_ street intersections (1 mile) **	.001	.037	.000	2.082	.000	.002
h_ bike route length (1 mile) *	1.078E-005	.007	.000	2.684	.000	.000
h_ number of parks (1 mile)	-.001	.861	.007	-.174	-.015	.012
h_ park areas (1 mile) *	-1.146E-007	.010	.000	-2.589	.000	.000
Gender						
Male	.741	.000	.058	12.749	.627	.855
Age						
5 to 12 years	-	-	-	-	-	-
13 to 17 years	-.365	.000	.031	-11.635	-.427	-.304
Household size						
2-person household	.266	.038	.128	2.079	.015	.517
3-person household	.036	.240	.031	1.176	-.024	.097
4-or-more-person household	-	-	-	-	-	-
Vehicles available						
No vehicles available	.342	.118	.219	1.562	-.087	.771
1 vehicle available	.169	.003	.056	3.019	.059	.279
2 vehicles available	-.002	.939	.024	-.077	-.048	.044
3 or more vehicles available	-	-	-	-	-	-
Annual household incomes						
incomes less than $25,000	.855	.000	.111	7.711	.638	1.072
incomes $25,000 -$50,000	.262	.000	.046	5.692	.172	.352
incomes $50,000 -$100,000	.058	.016	.024	2.419	.011	.105
incomes more than $100,000	-	-	-	-	-	-
Number of household bicycle						
One household bicycle	-.950	.000	.092	-10.275	-1.131	-.769
Two household bicycles	-.309	.000	.037	-8.411	-.381	-.237
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, youngest child 0-5	.178	.084	.103	1.731	-.024	.380
2+ adults, youngest child 0-5	-	-	-	-	-	-
one adult, youngest child 6-17	-.137	.000	.037	-3.718	-.209	-.065
2+ adults, youngest child 6-17	-.039	.001	.012	-3.206	-.063	-.015
N	12041					
R-square	0.053					
Adjusted R-square	0.051					

Cycling times in one week for schoolchildren

Variables	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
Constant	2.206	.000	.200	11.043	1.815	2.598
Built environment features						
Single-family homes	-	-	-	-	-	-
Multiple-family homes	-.093	.117	.059	-1.567	-.209	.023
h_ residential density (1 mile)	1.446	.971	39.859	.036	-76.684	79.576
h_ employment density (1 mile)	-14.625	.613	28.922	-.506	-71.317	42.068
h_ phy land use density (1 mile)	-.119	.521	.185	-.642	-.482	.244
h_ activity mix (0.25 mile)	.045	.850	.236	.189	-.417	.507
h_ activity mix (1 mile)	.261	.388	.302	.862	-.332	.853
*h_ street intersections (1 mile) **	.001	.052	.000	1.939	.000	.002
h_ bike route length (1 mile)	9.305E-007	.882	.000	.148	.000	.000
h_ number of parks (1 mile)	-.005	.571	.009	-.567	-.023	.013
h_ park areas (1 mile)	-5.205E-008	.345	.000	-.945	.000	.000
s_ residential density (1 mile) *	-144.825	.000	40.831	-3.547	-224.861	-64.789
s_ employment density (1 mile)	-5.589	.839	27.552	-.203	-59.596	48.418
s_ phy land use density (1 mile)	-.092	.636	.195	-.473	-.473	.289
*s_ activity mix (0.25 mile) **	-.375	.085	.218	-1.721	-.802	.052
s_ activity mix (1 mile)	-.034	.914	.311	-.108	-.644	.576
s_ street intersections (1 mile)	.000	.614	.000	-.505	-.001	.001
**s_ bike route length (1 mile) **	1.390E-005	.022	.000	2.290	.000	.000
s_ number of parks (1 mile)	.005	.577	.009	.557	-.013	.023
S_park areas (1 mile)	-9.297E-008	.146	.000	-1.452	.000	.000
Gender						
Male	.767	.000	.061	12.555	.647	.886
Age						
5 to 12 years	-	-	-	-	-	-
13 to 17 years	-.345	.000	.034	-10.218	-.412	-.279
Household size						
2-person household	.266	.045	.133	2.004	.006	.527
3-person household	.041	.201	.032	1.280	-.022	.104
4-or-more-person household	-	-	-	-	-	-
Vehicles available						
No vehicles available	.487	.034	.229	2.126	.038	.935
1 vehicle available	.205	.001	.059	3.459	.089	.321
2 vehicles available	.007	.791	.025	.265	-.042	.055
3 or more vehicles available	-	-	-	-	-	-
Annual household incomes						
incomes less than $25,000	.873	.000	.118	7.378	.641	1.105
incomes $25,000 -$50,000	.261	.000	.049	5.333	.165	.357
incomes $50,000 -$100,000	.061	.016	.025	2.401	.011	.111
incomes more than $100,000	-	-	-	-	-	-
Number of household bicycle						
One household bicycle	-.929	.000	.097	-9.571	-1.119	-.739
Two household bicycles	-.313	.000	.039	-8.105	-.389	-.237
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, youngest child 0-5	.139	.200	.109	1.283	-.074	.353
2+ adults, youngest child 0-5	-	-	-	-	-	-
one adult, youngest child 6-17	-.147	.000	.039	-3.815	-.222	-.071
2+ adults, youngest child 6-17	-.041	.001	.013	-3.179	-.067	-.016
N	11219					
R-square	0.055					
Adjusted R-square	0.052					

Cycling times in one week for all adults

Variables	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
Constant	.437	.000	.076	5.730	.287	.586
Built environment features						
Single-family homes	-	-	-	-	-	-
Multiple-family homes	-.009	.691	.022	-.398	-.053	.035
h_ residential density (1 mile) * **	-45.321	.000	12.811	-3.538	-70.431	-20.211
h_ employment density (1 mile)	-9.550	.270	8.661	-1.103	-26.526	7.425
h_ phy land use density (1 mile)	.001	.985	.055	.018	-.106	.108
h_ activity mix (0.25 mile)	-.003	.973	.079	-.034	-.158	.152
**h_ activity mix (1 mile) ** **	.222	.023	.098	2.267	.030	.413
h_ street intersections (1 mile) * **	.001	.000	.000	7.058	.001	.001
h_ bike route length (1 mile) * **	9.429E-006	.000	.000	6.352	.000	.000
h_ number of parks (1 mile)	-.002	.497	.002	-.679	-.006	.003
h_ park areas (1 mile)	-2.205E-008	.178	.000	-1.348	.000	.000
grav_job_access (5 mile to 50 mile) * **	-5.737E-007	.000	.000	-4.818	.000	.000
grav_job_access (5 mile) * **	1.387E-006	.000	.000	3.744	.000	.000
Gender						
Male	.556	.000	.021	26.240	.514	.597
Age						
18 to 34 years	.372	.000	.036	10.419	.302	.442
35 to 44 years	.072	.000	.019	3.826	.035	.109
45 to 54 years	.047	.000	.011	4.390	.026	.068
55 to 64 years	-	-	-	-	-	-
65 years and over	-.026	.002	.009	-3.040	-.044	-.009
Education						
not high school graduated or less	-.112	.028	.051	-2.199	-.212	-.012
high school graduates	-.005	.780	.017	-.279	-.039	.029
with some college credit but no degree	-.013	.244	.011	-1.164	-.035	.009
with associate or technical school degree	-.022	.027	.010	-2.207	-.041	-.002
hold bachelor's or undergraduate degree	-	-	-	-	-	-
hold graduated degree	.028	.000	.005	5.453	.018	.038
Household size						
1-person household	-	-	-	-	-	-
2-person household	.096	.000	.020	4.759	.057	.136
3-person household	.032	.002	.011	3.033	.011	.053
4-or-more-person household	-	-	-	-	-	-
Vehicle available						
No vehicles available	2.023	.000	.078	25.888	1.870	2.177
1 vehicle available	.307	.000	.020	15.614	.269	.346
2 vehicles available	.038	.000	.009	4.327	.021	.055
3 or more vehicles available	-	-	-	-	-	-
Home ownership						
Home owner	-.126	.000	.035	-3.575	-.195	-.057
Annual household incomes						
incomes less than $25,000	.082	.080	.047	1.751	-.010	.175
incomes $25,000 -$50,000	.036	.045	.018	2.001	.001	.071
incomes $50,000 -$100,000	.014	.107	.009	1.614	-.003	.031
incomes more than $100,000	-	-	-	-	-	-
Number of household bicycle						
One household bicycle	-.867	.000	.029	-29.738	-.924	-.810
Two household bicycles	-.295	.000	.013	-22.237	-.321	-.269
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, 18-64, no children	.331	.000	.065	5.074	.203	.458

2+ adults, at least one adult 18-64, no children	-	-	-	-	-	-
one adult, youngest child 0-5	-.090	.226	.074	-1.211	-.236	.056
2+ adults, youngest child 0-5	-.052	.000	.011	-4.768	-.073	-.031
one adult, youngest child 6-17	-.105	.000	.021	-5.031	-.147	-.064
2+ adults, youngest child 6-17	-.034	.000	.006	-5.859	-.045	-.023
one adult, over 64, no children	.061	.000	.016	3.920	.030	.091
2+ adults, all adults over 64, no children	.008	.331	.008	.971	-.008	.024
N	39353					
R-square	0.083					
Adjusted R-square	0.083					

Cycling times in one week for employed-adults

Variables	Coefficients	p-value	S.E.	t-statistic	CI 95% for coefficients	
					Lower	Upper
Constant	.460	.000	.115	3.986	.234	.686
Built environment features						
Single-family homes	-	-	-	-	-	-
Multiple-family homes	-.019	.513	.029	-.654	-.076	.038
h_ residential density (1 mile) ***	-61.040	.000	17.091	-3.571	-94.540	-27.541
*h_ employment density (1 mile) **	-19.966	.071	11.040	-1.809	-41.605	1.672
h_ phy land use density (1 mile)	-.031	.673	.073	-.422	-.175	.113
h_ activity mix (0.25 mile)	-.013	.898	.104	-.128	-.217	.190
h_ activity mix (1 mile) **	.326	.012	.130	2.516	.072	.580
h_ street intersections (1 mile) ***	.001	.000	.000	4.823	.001	.001
h_ bike route length (1 mile) ***	7.782E-006	.000	.000	3.699	.000	.000
h_ number of parks (1 mile)	.001	.702	.003	.382	-.005	.007
h_ park areas (1 mile)	-3.282E-008	.139	.000	-1.480	.000	.000
grav_job_access (5 mile to 50 mile) ***	-5.395E-007	.001	.000	-3.292	.000	.000
grav_job_access (5 mile) ***	1.944E-006	.000	.000	4.037	.000	.000
w_ residential density (1 mile)	-13.176	.267	11.880	-1.109	-36.460	10.109
w_ employment density (1 mile)	-3.196	.360	3.492	-.915	-10.040	3.648
w_ phy land use density (1 mile)	.089	.242	.076	1.169	-.060	.237
w_ activity mix (0.25 mile) **	-.225	.019	.096	-2.338	-.413	-.036
w_ activity mix (1 mile)	.102	.407	.123	.830	-.140	.344
w_ street intersections (1 mile) ***	.000428	.005	.000	2.796	.000	.001
w_ bike route length (1 mile) ***	8.163E-006	.000	.000	4.347	.000	.000
w_ number of parks (1 mile) **	-.008	.023	.004	-2.272	-.015	-.001
w_ park areas (1 mile)	-1.388E-008	.592	.000	-.536	.000	.000
Gender						
Male	.523	.000	.028	18.577	.468	.578
Age						
18 to 34 years	.279	.000	.042	6.699	.197	.360
35 to 44 years	.028	.194	.021	1.300	-.014	.069
45 to 54 years	-	-	-	-	-	-
55 to 64 years	-.023	.027	.010	-2.208	-.043	-.003
65 years and over	-.026	.145	.018	-1.459	-.061	.009
Education						
not high school graduated or less	-.126	.073	.071	-1.792	-.265	.012
high school graduates	-.028	.228	.023	-1.205	-.073	.017
with some college credit but no degree	-.006	.698	.015	-.388	-.034	.023
with associate or technical school degree	-.012	.343	.013	-.949	-.037	.013
hold bachelor's or undergraduate degree	-	-	-	-	-	-
hold graduated degree	.025	.000	.006	3.927	.013	.038
Household size						
1-person household	-	-	-	-	-	-
2-person household	.095	.000	.027	3.578	.043	.147
3-person household	.034	.011	.013	2.551	.008	.061
4-or-more-person household	-	-	-	-	-	-
Vehicle available						
No vehicles available	2.983	.000	.113	26.480	2.762	3.203
1 vehicle available	.422	.000	.027	15.744	.370	.475
2 vehicles available	.037	.001	.011	3.295	.015	.060
3 or more vehicles available	-	-	-	-	-	-
Home ownership						
Home owner	-.108	.016	.045	-2.402	-.195	-.020
Number of household bicycle						
One household bicycle	-.880	.000	.038	-23.073	-.955	-.805

Two household bicycles	-.306	.000	.017	-17.885	-.339	-.272
Three or more household bicycles	-	-	-	-	-	-
Household life stage						
one adult, 18-64, no children	.156	.063	.084	1.857	-.009	.320
2+ adults, at least one adult 18-64, no children	-	-	-	-	-	-
one adult, youngest child 0-5	-.095	.311	.094	-1.014	-.280	.089
2+ adults, youngest child 0-5	-.043	.002	.014	-3.103	-.070	-.016
one adult, youngest child 6-17	-.159	.000	.026	-6.221	-.209	-.109
2+ adults, youngest child 6-17	-.026	.000	.007	-3.493	-.041	-.011
one adult, over 64, no children	.029	.325	.029	.985	-.028	.086
2+ adults, all adults over 64, no children	-.026	.142	.018	-1.468	-.061	.009
N	23614					
R-square	0.099					
Adjusted R-square	0.097					

Elasticity analysis coefficients report

Built environment features	Children		Adults	
	All children	Children who go to school	All adults	Employed-adults
Home				
residential density (1 mile)	-0.142025 (±0.004241)		-0.171488 (±0.086426)	-0.209405 (±0.064828)
employment density (1 mile)				-0.026093 (±0.006653)
activity mix (1 mile)			0.082175 (±0.043787)	0.186702 (±0.060025)
street intersections (1 mile)	0.123786 (±0.002204)	0.130079 (±0.007816)	0.295200 (±0.155684)	0.378731 (±0.113760)
bike route length (1 mile)	0.052544 (±0.000806)		0.157021 (±0.075353)	0.145281 (±0.045220)
park areas (1 mile)	-0.037304 (±0.002515)			
Job accessibility (5 to 50 miles)			-0.144934 (±0.087646)	-0.114596 (±0.033599)
Job accessibility (5 miles)			0.109547 (±0.053939)	0.151890 (±0.042811)
School/Workplace				
residential density (1 mile)		-0.192445 (±0.018425)		
activity mix (0.25 mile)		-0.073737 (±0.002884)		-0.172040 (±0.058784)
street intersections (1 mile)				0.164248 (±0.042181)
bike route length (1 mile)		0.072866 (±0.002698)		0.186578 (±0.071027)
number of parks (1 mile)				-0.073994 (±0.036186)